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Methodology for the Design and Optimal Placement of Point Detectors in a Distributed Detection System for Remote Defence Against Biological Warfare Agent Releases

By:

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Defence Research Establishment Suffield

February 1998

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METHODOLOGY FOR THE DESIGN AND OPTIMAL PLACEMENT OF POINT DETECTORS IN A DISTRIBUTED DETECTION SYSTEM FOR REMOTE DEFENCE AGAINST BIOLOGICAL WARFARE AGENT RELEASES

by

Eugene Yee

PCN No. 051SP

ABSTRACT

This report deals with the design and performance evaluation of a distributed detection system for a dispersing biological warfare (BW) cloud embedded in the natural aerosol component of the background air. The distributed system employs a number of physically separated BW agent point detectors (sentries) located within some target region and a data fusion center that provides the final decision as to the presence or absence of the bio-target by combining the individual localized decisions from the various point detectors using a prespecified combining strategy. In this system, each detector implements a generalized likelihood ratio test on its own localized observations to test for the presence or absence of a bio-target. These localized detection decisions are then transmitted to a data fusion center where they are logically combined to yield a global detection decision for the distributed system. The optimization of the global detection performance of the distributed system is derived by application of the Lagrange multipliers method, whereby the global probability of detection for the system is maximized subject to the constraint that the global probability of false alarm is maintained at a prespecified level (viz., at a constant and tolerable false-alarm rate). A number of combining strategies are investigated in order to determine some overall system optimality for detection. It is found that the optimal detection strategy for each individual BW agent detector in the distributed system depends on the strategy of all the other detectors, as well as on the structure of the data fusion center. Explicit numerical results, in the form of the probability of detection versus signal-to-noise ratio for several preassigned false-alarm probabilities and sample sizes [which determine the maximum allowable mean time to detection], are presented for the case of a distributed system consisting of three BW agent detectors. The results are compared to the detection performance that is achievable using only a single detector. Finally, the problem of the correct placement of the individual BW agent detectors in the distributed system in order to achieve a specified detection performance is addressed. In particular, a method for the determination of the dosage probabilities at fixed points in the target region is developed and used to place BW agent detectors in a distributed system.

EXECUTIVE SUMMARY

Title: Methodology for the Design and Optimal Placement of Point Detectors in a Distributed Detection System for Remote Defence Against Biological Warfare Agent Releases

Author: Eugene Yee

Introduction: There are, quite rightly, growing concerns world-wide about the dangers, both actual and potential, of the use of biological warfare (BW) agents. In particular, the May 1997 *Report of the Quadrennial Defence Review* (Department of Defence, USA) concluded that the likelihood of encountering BW agents in a specific military operation increases with each year and will probably be a likely condition of future warfare. The low cost, low technology, and relative ease of producing BW agents, and our national policy to maintain appropriate defences against such threats imply that the BW agent threat must be taken seriously. Indeed, the use of BW agents against Canadian forces is probably more likely than it was in the past given the proliferation of BW agent capabilities among various countries.

The lack of direct BW agent experience implies that quantified military hazard assessment of BW agents must be approached primarily as a description of possibilities, largely based on considerations of past research and development activities in this area and supported by mathematical modelling of the possible risks to an individual or a troop of being exposed to concentrations of a dispersing BW agent cloud released from some form of delivery/munition system. Depending on the release mode, BW agent sources can include transient line and point sources produced by spraying from a low-flying aircraft or some stationary platform, as well as multiple instantaneous point sources produced by sub-munitions and bomblets. Furthermore, BW agents are extremely potent, and attacks that are initiated by disseminating relatively small quantities of the agent either overtly or covertly from a fixed or mobile platform such as a truck, ship, or fixed-wing aircraft can produce a significant hazard range. In consequence, in order to develop an effective defence against BW agent attack, it is necessary to understand the course and consequences of such an attack , so that the design and evaluation of detection and warning systems can be facilitated. The prediction of what will happen to a BW agent after it has been disseminated from a munition system and the evaluation of expected concentration levels available for BW agent detection systems located downwind of the release position can only be obtained

using computer simulation models.

When a BW agent is released into the atmosphere, the immediate fate of the agent largely depends on the local meteorological conditions. In almost all cases, drift and turbulent diffusion will spread the BW agent cloud over a large area. Depending on the atmospheric turbulence, the BW agent cloud will become more or less dispersed. However, it must be recognized that local micrometeorology can easily dominate the drift and diffusion process. The turbulence is dependent on the ground topography, the temperature in the air mass, the wind speed, etc. and the actual distribution and concentration of a BW agent in a dispersing cloud can vary greatly from place to place. Any BW agent detection and warning system must be designed to recognize and account for these possibilities. In view of this, the theory of distributed detection of BW agents is developed in this report. Furthermore, it is shown how a mathematical model for simulating the turbulent dispersion of BW agents in the atmosphere can be applied to formulate a rational and practical methodology for the optimal placement of individual BW agent detectors in a remote distributed detection system.

Results: This report deals with the design and performance evaluation of a distributed detection system for a dispersing biological warfare (BW) cloud embedded in the natural aerosol component of the background air. The distributed system employs a number of physically separated BW agent point detectors (sentries) located within some target region and a data fusion center that provides the final decision as to the presence or absence of the bio-target by combining the individual localized decisions from the various point detectors using a prespecified combining strategy. In this system, each detector implements a generalized likelihood ratio test on its own localized observations to test for the presence or absence of a bio-target. These localized detection decisions are then transmitted to a data fusion center where they are logically combined to yield a global detection decision for the distributed system. The optimization of the global detection performance of the distributed system is derived by application of the Lagrange multipliers method, whereby the global probability of detection for the system is maximized subject to the constraint that the global probability of false alarm is maintained at a prespecified level (viz., at a constant and tolerable false-alarm rate). A number of combining strategies are investigated in order to determine some overall system optimality for detection. It is found that the optimal detection strategy for each individual BW agent detector in the distributed system depends on the strategy of all the other detectors, as well as on the structure of the data

fusion center. Explicit numerical results, in the form of the probability of detection versus signal-to-noise ratio for several preassigned false-alarm probabilities and sample sizes [which determine the maximum allowable mean time to detection], are presented for the case of a distributed system consisting of three BW agent detectors. The results are compared to the detection performance that is achievable using only a single detector. Finally, the problem of the correct placement of the individual BW agent detectors in the distributed system in order to achieve a specified detection performance is addressed. In particular, a method for the determination of the dosage probabilities at fixed points in the target region is developed and used to place BW agent detectors in a distributed system.

Significance of Results: The design and optimal placement of BW agent detectors in a distributed system for the space-time detection of weak target bio-aerosol signals from a dispersing BW agent cloud embedded in a general aerosol background clutter have been investigated. The results of this report provide a general framework for obtaining potential improvements of distributed systems for the remote detection of BW agent releases by using appropriate fusion rules or combining strategies at the data fusion center. These combining strategies can be used to improve the probability of detection while maintaining a small (and, hence, tolerable) false-alarm rate, and coupled with a method for the correct placement of the individual BW agent detectors of the distributed system in the target region, it is now possible to maximize detection performance for a given detection environment and BW agent scenario. An innovation of the current methodology is the use of a state-of-the-art atmospheric dispersion model to determine the area covered by a certain critical dosage with a given probability, and to use this information for the optimal placement of BW agent detectors in a distributed system. In other words, a transport and diffusion model for atmospheric dispersion is used to quantify the detection enviroment, and this information is then used to obtain explicit solutions for optimum thresholds and strategies.

Of particular significance is the fact that, for a given set of operating conditions (e.g., signal-to-noise ratio, sample size, false-alarm probability, etc.), the distributed system always exhibits better detection performance than that afforded by a single detector system. Hence, in the optimal remote detection of BW agents, it is preferable to have many low-cost BW agent detectors configured to act as a distributed system, rather than a few high-cost BW agent detectors each of which is configured to act in a stand-alone mode. Furthermore, distributed detection systems are expected to be more reliable and immune to background

clutter than stand-alone systems. While these properties are due to inherent redundancy in a distributed system, the enhanced performance of distributed systems essentially derives from the coverage and spatial-temporal diversity afforded by the system configuration. Finally, within the general framework of distributed detection systems, our analysis establishes that the optimal decision strategy of any BW agent detection system must take into account a number of related factors: namely, the correct placement of the individual detectors within the target region and the recognition that even with the correct placement of detectors, the optimum decision strategy of any detector must take into account the operating environments and performances of all other detectors in the system, as well as the structure of the fusion center.

Future Work: Future work on the distributed detection of BW agents is possible in several directions. Firstly, it is recommended that the proposed methodology for the design and placement of BW agent detectors in a distributed system be integrated with a practical probabilistic model for turbulent diffusion such as the Second-order Closure Integrated PUFF (SCIPUFF) model developed by Aeronautics Research Associates Princeton (ARAP) under the sponsorship of the U.S. Defence Special Weapons Agency (DSWA). Secondly, it would be meaningful to search for sub-optimum, and possibly robust designs involving far less complex computations than those proposed for the current methodology. Finally, it would be interesting to look at different topologies of distributed BW agent detection systems, and investigate whether certain topologies are more appropriate for use in defending against certain BW agent release scenarios.

TABLE OF CONTENTS

I. INTRODUCTION

There are, quite rightly, growing concerns world-wide about the dangers, both actual and potential, of the use of biological warfare (BW) agents. In particular, the likelihood of encountering BW agents in a specific military operation increases with each year [1,2]. The low cost, low technology, and relative ease of producing BW agents, and our national policy to maintain appropriate defences against such threats imply that the BW threat must be taken seriously. Indeed, the use of BW agents against Canadian forces is probably more likely than it was in the past given the proliferation of BW agent capabilities among various countries.

The lack of direct BW agent experience implies that quantified military hazard assessment of BW agents must be approached primarily as a description of possibilities, largely based on considerations of past research and development activities in this area and supported by mathematical modelling of the possible risks to an individual or a troop of being exposed to concentrations of a dispersing BW agent cloud released from some form of delivery/munition system. Depending on the release mode, the BW agent sources can include transient line and point sources (e.g., spraying from a low-flying aircraft or some stationary platform) as well as multiple instantaneous point sources (e.g, sub-munitions and bomblets). Furthermore, BW agents are extremely potent, and attacks that are initiated by disseminating relatively small quantities of the agent either overtly or covertly from a fixed or mobile platform (e.g., truck, ship, fixed-wing aircraft, etc.) can produce a significant hazard range (i.e., the maximum downwind distance that might be reached by a militarily significant concentration of agent over a given exposure time to produce an infective or effective dose under particular release conditions). In consequence, in order to develop an effective defence against a BW agent attack, it is necessary to understand the course and consequences of such an attack (e.g., transport and degree of contamination) so that the design and evaluation of detection and warning systems can be facilitated. The prediction of what will happen to a BW agent after it has been disseminated from a munition system and the evaluation of expected concentration levels available for BW agent detection systems located downwind of the release position can only be obtained using computer simulation models.

When a BW agent is released into the atmosphere, the immediate fate of the agent largely depends on the local meteorological conditions. In almost all cases, drift and tur-

bulent diffusion will spread the BW agent cloud over a large area. Depending on the atmospheric turbulence, the BW agent cloud will become more or less dispersed. However, it must be recognized that local micrometeorology can easily dominate the drift and diffusion process. The turbulence is dependent on the ground topography, the temperature in the air mass, the wind speed, etc. and the actual distribution and concentration of a BW agent in a dispersing cloud can vary greatly from place to place. Any BW agent detection and warning system must be designed to recognize and account for these possibilities. In view of this, the theory of distributed detection of BW agents is developed in this report. Furthermore, it is shown how a mathematical model for simulating the turbulent dispersion of BW agents in the atmosphere can be applied to formulate a rational and practical methodology for the optimal placement of individual BW agent detectors in a remote distributed detection system.

The consideration of a distributed system as opposed to the single detector scheme for BW agent detection is motivated primarily by the potentially improved detection performance at a preassigned false-alarm probability that can be achieved using multiple detectors. Indeed, the performance of a single sensor detection system is rather limited because the performance of the sensor is based on its local operating conditions. Consequently, the use of a distributed sensor detection scheme can make the detection performance robust in addition to providing an improvement in the detection probability for a fixed false-alarm rate. However, the potential improvement in detection performance achievable in a distributed system requires a careful examination of two factors; namely, (1) the design of the data processing scheme used to process the observations received by the various detectors; and, (2) the development of a methodology for the optimal placement of the individual detectors of the distributed system within the target region in order to account for the influences of a number of meteorological parameters (wind speed, turbulence, topography, etc.) that determine the precise distribution and concentration of a dispersing BW agent cloud. Neglecting either one of these two factors can lead to a serious degradation in the overall performance of the BW agent detection system.

This study focusses on the formulation, design, and analysis of a distributed and decentralized detection scheme for a BW agent that has been transported from some remote upwind source location over the receptor point by the movements of the wind. In this approach, a number of peripheral BW agent detectors (e.g., sentries) are deployed over a potential target area. The individual detectors are assumed to process their local observations through some optimal threshold detection algorithm (e.g., a likelihood ratio detector)

to produce their own local detection decisions. The detection decisions from the individual detectors are then transmitted to the data fusion center which then logically combines these local decisions to decide on the presence or absence of the BW agent. Within this framework, we study the optimal design for combining decisions emanating from peripherally located detectors. The principal objective is to formulate a globally optimum detection algorithm for the distributed system as a whole, in terms of a number of relevant parameters; namely, the probability of detection for a preassigned false-alarm probability, the signal-to-noise ratio presented by the operating environment, the minimum mean time to detection, and the location or placement of the individual detectors or sentries within the designated target area. The principal task in this report is to combine all these relevant parameters to obtain the "macro-algorithms", so to speak, for the entire distributed BW agent detection system, and to analyze their expected performance measures (i.e., here probabilities of correct decisions) in such a way as to incorporate the controlling physical factors which the detection environment and release scenario impose (and which is characterized here by the application of mathematical models for the prediction and assessment of BW agent hazards in the atmosphere).

II. DETECTION PERFORMANCE OF A SINGLE DETECTOR

The detectors (sentries) in the distributed system are assumed to act independently of each other. In order to characterize the detection performance of the distributed system, it is necessary to first model the detection performance for a single detector. To proceed further, it is necessary to either measure the detection performance of the detector as a function of the signal-to-noise ratio of the operating environment, or to develop a theoretical model that can be used to predict the detection performance. In this section, we do not present an analysis of any specific BW agent detector. Rather, we will characterize the detection performance of a generic BW agent detector in order to use it as an example of the proposed methodology for distributed system design and detector placement.

To this purpose, consider a generic BW agent detector which samples for a total duration T to produce count data as a set of numbers $\{F(j), j = 1, 2, \ldots, J\}$. Normally, the count data is related to the time-averaged concentration measured over the sampling interval (e.g., the count in each sample interval is proportional to the number of particles, N, in a given volume, $R\tau$, of air where R is the known rate at which air is drawn through the detector and τ is the sampling interval, with the constant of proportionality here dependent on a correction for the efficiency of collection, retention, or absorption). The count data

corresponding to the target signal can be viewed as being proportional to the dosage $\mathcal{D}$ accumulated by the detector during the time τ, viz.

$$F(t_j) \equiv F(j) \propto \mathcal{D}(t_j; \tau) = \int_{t_j}^{t_j+\tau} \chi(t')\, dt', \tag{1}$$

where $\chi(t)$ is the instantaneous concentration (number of particles per unit volume) at time t. Furthermore, the count data sampled by the detector are assumed to depend linearly on the characteristic signal that is used to detect the bio-aerosol (e.g., fluorescence energy, etc.). As an example, in laser-induced fluorescence techniques for BW agent detection, the count data would be related directly to bio-fluorescence energy (e.g., number of fluorescing photons) in a characteristic emission band [3]. The sample counts are random variables. It is assumed that the count $F(j)$ obtained during the jth sampling interval (reception or snapshot) is a Poisson random variable. Furthermore, it is assumed that counts obtained during disjoint sampling intervals (i.e., exposures) are mutually independent random variables.

The count data are assumed to consist of the sum of a target bio-aerosol signal (e.g., BW agent) and an ambient interfering background clutter aerosol signal (e.g., non-microbiological aerosols, pollen, dust, etc.) that is unavoidably received from the natural aerosol component present in the atmosphere. In this case, the count datum $F(j)$ is a Poisson random variable with parameter $\lambda^{(1)}(j) = S(j) + \lambda^{(0)}$. For simplicity, we take the target signal $S(j)$ to be equal to the partial dosage from the BW agent cloud accumulated during the sampling interval τ extending from t_j to $t_j + \tau$ (i.e., we ignore the collection efficiency of the sampler), so

$$S(j) = \mathcal{D}(j) \equiv \mathcal{D}(t_j; \tau) = \int_{t_j}^{t_j+\tau} \chi_s(t')\, dt',$$

where $\chi_s(t)$ is the instantaneous concentration contributed by the BW agent cloud (if present). We assume that the target signal contribution, $S(j)$, to the Poisson parameter $\lambda^{(1)}(j)$ is known *a priori*. In addition, it is assumed that the background clutter contribution, $\lambda^{(0)}$, to the Poisson parameter $\lambda^{(1)}(j)$ does not depend on j, viz., the background Poisson parameter is the same for all J aerosol samples obtained during the sampling time $T \equiv J\tau$. The primary goal is to detect the presence of the bio-target signal in a given realization of the received count data $\{F(j), j = 1, 2, \ldots, J\}$ (i.e., in the J aerosol samples collected during the sampling time T).

Since the bio-target signal may or may not be present in the received data sequence $\{F(j)\}_{j=1}^{J}$, this leads to the following binary hypothesis testing problem involving the choice

between the two hypotheses:

$$
\begin{aligned}
&H_0 : \lambda^{(1)}(j) = \lambda^{(0)};\\
&H_1 : \lambda^{(1)}(j) = S(j) + \lambda^{(0)}.
\end{aligned}
\tag{2}
$$

According to the classical theory of detection [4], it is desirable to implement a threshold signal detection receiver which realizes the likelihood ratio test. The likelihood ratio test is preferred because it possesses some nice asymptotic (i.e., large-sample size) properties such as unbiasedness, consistency, and constant false-alarm rate. With reference to Eq. (2), the likelihood ratio test decides H_1 (i.e., bio-target present) if

$$
\Lambda \equiv \frac{p\big(\{F(j)\}\big|H_1\big)}{p\big(\{F(j)\}\big|H_0\big)} > \Lambda_0,
$$

where Λ_0 is some threshold value and $p\big(\{F(j)\}\big|H_i\big)$ is the likelihood function for obtaining the count data $\big\{F(j), j = 1, 2, \ldots, J\big\}$ under hypothesis H_i ($i = 0, 1$). Hence, to detect the bio-target signal, we have to compare the detection statistic Λ with a threshold Λ_0, the "decision level". The exceedance of this decision level by Λ is an indication of the presence of the bio-target signal. For Poisson-distributed count data, it is simpler to use the log-likelihood ratio test which decides H_1 if

$$
\mathcal{L} \equiv \ln \Lambda = \ln\Big(p\big(\{F(j)\}\big|H_1\big)\Big) - \ln\Big(p\big(\{F(j)\}\big|H_0\big)\Big) > \mathcal{T},
$$

where $\mathcal{T} \equiv \ln \Lambda_0$ is the threshold for the transformed decision rule.

Because the count data $\big\{F(j), j = 1, 2, \ldots, J\big\}$ are assumed to be independently distributed, the computation of the log-likelihood ratio is straightforward. This results in the following test:

$$
\begin{aligned}
\mathcal{L} &= \ln \Lambda\\
&= \sum_{j=1}^{J} \left[F(j) \ln\left(1 + \frac{S(j)}{\lambda^{(0)}}\right) - S(j)\right] > \mathcal{T}.
\end{aligned}
\tag{3}
$$

The threshold, $\mathcal{T}$, is selected objectively using the Neyman-Pearson criterion [4]. In the Neyman-Pearson criterion, the probability of false alarm in constrained to an acceptable value and under this constraint, the decision rule is designed to maximize the probability of detection. The false-alarm probability, P_{FA}, (level of the test) and the detection probability, P_{D}, (power of the test) are defined as

$$
P_{\mathrm{FA}} \equiv \Pr\big\{\mathcal{L} > \mathcal{T}\big|H_0\big\}, \tag{4a}
$$

and

$$P_{\mathrm{D}} \equiv \Pr\{\mathcal{L} > \mathcal{T} | H_1\}, \tag{4b}$$

where $\Pr\{\cdot\}$ denotes the "probability that".

To select a threshold level that corresponds to some prespecified false-alarm probability requires a knowledge of the probabilistic characteristics of the detection statistic $\mathcal{L}$. The determination of $\mathcal{T}$ using the exact statistics of $\mathcal{L}$ (which is described by a multivariate Poisson probability function) is a formidable problem. However, when the number of counts in a sample is sufficiently largely (e.g., $\lambda^{(1)}(j) \gtrsim 50$), the Poisson probability function for the count data can be approximated very well with the Gaussian distribution. In view of this, we apply the Lindelberg condition [5] of the central limit theorem to the sum of random variables to argue that the log-likelihood ratio, $\mathcal{L}$, exhibited in Eq. (3) is asymptotically Gaussian-distributed under both H_0 and H_1 in accordance to the following description:

$$\begin{aligned} &\mathcal{L} \sim N(\mu_0, \sigma_0) \qquad \text{under } H_0; \\ &\mathcal{L} \sim N(\mu_1, \sigma_1) \qquad \text{under } H_1. \end{aligned} \tag{5}$$

Here, $N(\mu, \sigma)$ denotes the Gaussian distribution with mean μ and standard deviation σ. The mean and variance of the log-likelihood ratio under H_0 and H_1 can be shown to have the following forms:

$$\mu_0 \equiv \mathbf{E}(\mathcal{L}|H_0) = \sum_{j=1}^{J} \left[\lambda^{(0)} \ln\left(1 + \frac{S(j)}{\lambda^{(0)}}\right) - S(j)\right], \tag{6}$$

$$\mu_1 \equiv \mathbf{E}(\mathcal{L}|H_1) = \mathbf{E}(\mathcal{L}|H_0) + \sum_{j=1}^{J} S(j) \ln\left(1 + \frac{S(j)}{\lambda^{(0)}}\right), \tag{7}$$

$$\sigma_0^2 \equiv \mathrm{Var}(\mathcal{L}|H_0) = \sum_{j=1}^{J} \lambda^{(0)} \ln^2\left(1 + \frac{S(j)}{\lambda^{(0)}}\right), \tag{8}$$

and

$$\sigma_1^2 \equiv \mathrm{Var}(\mathcal{L}|H_1) = \mathrm{Var}(\mathcal{L}|H_0) + \sum_{j=1}^{J} S(j) \ln^2\left(1 + \frac{S(j)}{\lambda^{(0)}}\right). \tag{9}$$

Here, $\mathbf{E}(\cdot)$ denotes mathematical expectation, and $\mathrm{Var}(\cdot)$ denotes variance. An examination of Eqs (6)–(9) shows that the variance of $\mathcal{L}$ under H_1 approaches the variance of $\mathcal{L}$ under H_0 as $J \to \infty$ and $S(j) \to 0$ (for all j) at a rate that is faster than the convergence of the means under the two hypotheses. Consequently, in this limit, the decision test for $\mathcal{L}$ reduces

to a test between two Gaussian variates with different means and the same variance. In this case, the detection performance is completely embodied in the detectability parameter

$$r \equiv \frac{\mathbf{E}(\mathcal{L}|H_1) - \mathbf{E}(\mathcal{L}|H_0)}{\sqrt{\mathrm{Var}(\mathcal{L}|H_0)}}.$$

Eqs (5)–(9) provide the basis for an easily-evaluated computation for P_{FA} and P_{D}. It is now a straightforward exercise to show that the value of the threshold, $\mathcal{T}$, required to maintain a desired false-alarm probability of α (significance level) can be determined from the solution of the following equation [cf. Eqs (4a) and (5)]:

$$\begin{aligned} P_{\mathrm{FA}} = \alpha &= \frac{1}{\sqrt{2\pi}\sigma_0} \int_{\mathcal{T}}^{\infty} \exp\Big(-\frac{1}{2\sigma_0^2}\big(x-\mu_0\big)^2\Big)\, dx \\ &= 1 - \Phi\Big(\frac{\mathcal{T}-\mu_0}{\sigma_0}\Big), \end{aligned} \tag{10a}$$

where

$$\Phi(x) \equiv \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\Big(-\frac{t^2}{2}\Big)\, dt \tag{10b}$$

is the cumulative standard normal distribution function. Hence,

$$\mathcal{T} = \mu_0 + \sigma_0 \Phi^{-1}\big(1-\alpha\big). \tag{11}$$

For the specified threshold, $\mathcal{T}$, the probability of detection, P_{D}, [cf. Eqs (4b) and (5)] is calculated as

$$\begin{aligned} P_{\mathrm{D}} &= \frac{1}{\sqrt{2\pi}\sigma_1} \int_{\mathcal{T}}^{\infty} \exp\Big(-\frac{1}{2\sigma_1^2}\big(x-\mu_1\big)^2\Big)\, dx \\ &= 1 - \Phi\Big(\frac{\mathcal{T}-\mu_1}{\sigma_1}\Big). \end{aligned} \tag{12}$$

It is interesting to note that for the stressing case where the signal intensity level is much less than the ambient background clutter intensity level, the probability of detection, P_{D}, for a fixed false-alarm probability, P_{FA}, is a monotonically increasing function of the quantity

$$\mathrm{SNR} \equiv \frac{1}{J} \sum_{j=1}^{J} \frac{S(j)}{\lambda^{(0)}}, \tag{13}$$

which we take to be the definition of the signal-to-noise ratio for our problem.

III. DISTRIBUTED SENSOR DETECTION AND DATA FUSION

In this section, the theory of distributed detection of BW agents is developed. To this end, let us consider the following two-stage hypothesis testing/detection procedure. In the first stage, the i-th local detector ($i = 1, 2, \ldots, n$) measures the local aerosol count data $\{F^i(j), j = 1, 2, \ldots, J_i\}$ and applies the likelihood ratio test to produce a local binary detection decision D_i ($i = 1, 2, \ldots, n$); viz.,

$$D_i = \begin{cases} 0, & \text{if detector } i \text{ decides } H_0 \text{ (bio-target absent locally);} \\ 1, & \text{if detector } i \text{ decides } H_1 \text{ (bio-target present locally).} \end{cases}$$

In the second stage, these binary detection decisions D_i ($i = 1, 2, \ldots, n$) are then transmitted to the data fusion center where they are processed through an appropriate fusion rule (combining strategy) to produce a global detection decision, D_G, for the presence or absence of the bio-target (i.e., a global inference); viz.,

$$D_G = \begin{cases} 0, & \text{decide bio-target absent, i.e., global decision } H_0; \\ 1, & \text{decide bio-target present, i.e., global decision } H_1. \end{cases}$$

It is assumed that the local detection decisions are mutually statistically independent, i.e., there is no direct communication between the local detector elements of the distributed system—the local detectors are only permitted to send the local detection decisions directly to the data fusion center (central processor, or equivalently, the command and control center). To summarize, the fusion center yields the global decision, D_G, based on the received decision vector containing the local decisions, viz., $\vec{D} = (D_1, D_2, \ldots, D_n)$. The global decision, D_G, is assumed to depend only on the local decision vector, $\vec{D}$, and not on the observations, $\{F^i(j), j = 1, 2, \ldots, J_i\}$, at the individual detectors.

The objective now is to determine a set of appropriate fusion or decision rules at the fusion center for the specification of a global decision that maximizes the system detection probability under a false-alarm probability constraint. Hence, the goal is to formulate the distributed Neyman-Pearson detection problem and then to derive the decision rules. Towards that goal, we seek to assign local detection thresholds $\mathcal{T}_i$ ($i = 1, 2, \ldots, n$), for the local (peripheral) likelihood ratio detectors in the system so that the global detection probability, P_{D}, at the fusion center (power of the system) is maximized while keeping the global false-alarm probability, P_{FA}, at a desired level, say α (level of the test). This constrained maximization problem can be solved by application of Lagrange's multiplier method which reduces in the present case to the maximization of the following Lagrange function L:

$$L(\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_n) = P_{\mathrm{D}}(\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_n) + \lambda\Big[P_{\mathrm{FA}}(\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_n) - \alpha\Big], \tag{14}$$

where λ is an undetermined Lagrange multiplier. The dependence of the global probabilities of detection and false alarm on the local detection thresholds $\{\mathcal{T}_i\}_{i=1}^{n}$ has been explicitly indicated in Eq. (14). Hence, the decision rules that maximize P_{D} for a given value of P_{FA} are likelihood ratio tests with thresholds to be determined.

To utilize Eq. (14) to determine the optimal detector structure requires explicit expressions for the global detection probability, P_{D}, and the global false-alarm probability, P_{FA}. The precise form of these global probabilities depends on the fusion rule used to combine the detection decisions, D_i, at the data fusion center. More precisely, the fusion rule is completely specified by the following transition probabilities:

$$F(D_1, D_2, \ldots, D_n) \equiv \Pr\{D_G = 1 | D_1, D_2, \ldots, D_n\}, \tag{15a}$$

and

$$G(D_1, D_2, \ldots, D_n) \equiv \Pr\{D_G = 0 | D_1, D_2, \ldots, D_n\}. \tag{15b}$$

In what follows, let P_{FA_i} and P_{D_i} denote the probabilities of false alarm and detection, respectively, for the i-th local detector. Obviously, these two probabilities are determined by the choice of the local detection thresholds $\mathcal{T}_i$ [cf. Eqs (10)–(12)]. The constraint $P_{\mathrm{FA}} = \alpha$ induces constraints on the individual P_{FA_i} and determines the level at each of the local detectors. Because P_D is an increasing function of P_{D_i} $(i = 1, 2, \ldots, n)$, to obtain the maximum value of P_{D}, it follows that each local detector should operate at its maximum achievable P_{D_i}, viz., use the most powerful test, for its given level P_{FA_i}.

Given the form of the transition probabilities defined in Eq. (15), expressions for the global probabilities can be determined in terms of the transition probabilities and the local probabilities of detection and false alarm as follows: (1) the global probability of false alarm, P_{FA},

$$\begin{aligned} P_{\mathrm{FA}} \equiv \Pr\{D_G = 1 | H_0\} &= \sum_{D_1, D_2, \ldots, D_n} \Pr\{D_G = 1 | \vec{D}\} \cdot \Pr\{\vec{D} | H_0\} \\ &= \sum_{D_1, D_2, \ldots, D_n} \Pr\{D_G = 1 | D_1, D_2, \ldots, D_n\} \cdot \prod_{i=1}^{n} \Pr\{D_i | H_0\} \\ &= \sum_{D_1, D_2, \ldots, D_n} F(D_1, D_2, \ldots, D_n) \cdot \prod_{M_0} (1 - P_{\mathrm{FA}_j}) \cdot \prod_{M_1} P_{\mathrm{FA}_k}; \end{aligned} \tag{16}$$

(2) the global probability of detection, P_{D},

$$P_{\mathrm{D}} \equiv \Pr\{D_G = 1 | H_1\} = \sum_{D_1, D_2, \ldots, D_n} \Pr\{D_G = 1 | \vec{D}\} \cdot \Pr\{\vec{D} | H_1\}$$

$$= \sum_{D_1, D_2, \ldots, D_n} \Pr\{D_G = 1 | D_1, D_2, \ldots, D_n\} \cdot \prod_{i=1}^{n} \Pr\{D_i | H_1\}$$

$$= \sum_{D_1, D_2, \ldots, D_n} F(D_1, D_2, \ldots, D_n) \cdot \prod_{M_0} (1 - P_{D_j}) \cdot \prod_{M_1} P_{D_k}; \quad (17)$$

and, (3) the global probability of miss, P_M,

$$P_M \equiv 1 - P_D = \sum_{D_1, D_2, \ldots, D_n} \Pr\{D_G = 0 | \vec{D}\} \cdot \Pr\{\vec{D} | H_1\}$$

$$= \sum_{D_1, D_2, \ldots, D_n} G(D_1, D_2, \ldots, D_n) \cdot \prod_{M_0} (1 - P_{D_j}) \cdot \prod_{M_1} P_{D_k}. \quad (18)$$

In Eqs (16)–(18), the index set $M_0 \equiv \{i : D_i = 0\}$; similarly, the index set $M_1 \equiv \{i : D_i = 1\}$. In other words, M_0 is the set of all local BW agent detectors that decide "bio-target absent", whereas M_1 is the set of all detectors that decide"bio-target present".

With these explicit expressions for P_D and P_{FA}, we are now in a position to maximize the Lagrange function L [cf. Eq. (14)] with respect to the local detection thresholds $\mathcal{T}_i$ $(i = 1, 2, \ldots, n)$. By the usual rules of calculus, this is accomplished by equating the partial derivative of L [cf. Eq. (14)] with respect to $\mathcal{T}_i$ to zero for $i = 1, 2, \ldots, n$. This leads to a system of n nonlinear equations in $(n+1)$ unknowns, namely, the local detection thresholds $\{\mathcal{T}_i\}$ and the Lagrange multiplier λ. Another independent equation results by equating the partial derivative of L with respect to λ equal to zero. This, as usual, simply encodes the constraint equation, i.e., $P_{FA} = \alpha$.

IV. SOME FUSION RULES AND PERFORMANCE ANALYSIS

It is not possible to obtain explicit solutions for the optimum detection thresholds $\mathcal{T}_i$ without a knowledge of the combining strategy at the fusion center. Hence, the local detection thresholds $\mathcal{T}_i$ can be determined using Lagrange's multiplier method once the fusion rule for combining the local detection decisions D_i $(i = 1, 2, \ldots, n)$ has been specified. As an illustration of the technique, we consider a combining strategy that is based on the k-out-of-n logical function; viz., if k or more local detectors decide H_1, then the global detection decision is to decide H_1. As a simple illustration of the technique, we consider a distributed system consisting of three local detectors. For this simple case, we will provide explicit results for the detection performance of the distributed system based on the k-out-of-n fusion rule. For a distributed system of three detectors (i.e., $n = 3$), we need to consider the 1-out-of-3 rule (OR rule), the 2-out-of-3 rule (MAJORITY rule), and the

3-out-of-3 rule (AND rule). In what follows, $(\mu_0^{(i)}, \sigma_0^{(i)})$ and $(\mu_1^{(i)}, \sigma_1^{(i)})$ denote the mean and standard deviation of the log-likelihood ratio statistic measured at the i-th local detector under hypotheses H_0 and H_1, respectively [cf. Eqs (6)–(9)].

Case 1: (OR rule) For this case, the components of the binary-valued state vector $\vec{D} \equiv (D_1, D_2, D_3)$ are combined at the data fusion center using the Boolean logic operator OR. Consequently, the associated transition probabilities are given by

$$F(\vec{D}) \equiv \Pr\{D_G = 1 | \vec{D}\} = \begin{cases} 0, & \text{if } |\vec{D}| = 0; \\ 1, & \text{otherwise.} \end{cases}$$

Or, equivalently,

$$G(\vec{D}) \equiv \Pr\{D_G = 0 | \vec{D}\} = \begin{cases} 1, & \text{if } |\vec{D}| = 0; \\ 0, & \text{otherwise.} \end{cases}$$

Here, $|\vec{D}| \equiv \sum_{i=1}^{3} D_i$ is the Hamming norm of the binary-valued vector $\vec{D}$. In other words, the data fusion center decides H_0 (bio-target absent) only if all the local detectors decide H_0.

For the case of the OR rule, the Neyman-Pearson decision rule is most easily expressed as the minimization of the global probability of miss, P_{M}, [which is equivalent to the maximization of the global probability of detection, $P_{\mathrm{D}} \equiv (1 - P_{\mathrm{M}})$] subject to the constraint that the global probability of false alarm, P_{FA}, be maintained at a desired level α (i.e., $P_{\mathrm{FA}} = \alpha$). In view of Eqs (10), (12), (14), (15), (16), and (18), the choice of the local detection thresholds, $\mathcal{T}_i$, to achieve optimum detection performance can be formulated as the minimization of the following Lagrange function:

$$\begin{aligned} L(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3) &= P_{\mathrm{M}} + \lambda\Big[(1 - P_{\mathrm{FA}}) - (1 - \alpha)\Big] \\ &= \prod_{i=1}^{3} \Phi\left(\frac{\mathcal{T}_i - \mu_1^{(i)}}{\sigma_1^{(i)}}\right) + \lambda\left[\prod_{i=1}^{3} \Phi\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) - (1 - \alpha)\right]. \end{aligned}$$

Taking the partial derivatives $\partial L / \partial \mathcal{T}_i$ $(i = 1, 2, 3)$ and $\partial L / \partial \lambda$ and equating these results to zero, leads to the following set of design relationships for the specification of the local detection thresholds required to achieve optimum global detection performance:

$$\begin{aligned} 0 = &\frac{1}{\sigma_1^{(i)}} \Phi'\left(\frac{\mathcal{T}_i - \mu_1^{(i)}}{\sigma_1^{(i)}}\right) \prod_{\substack{j=1 \\ j \neq i}}^{3} \Phi\left(\frac{\mathcal{T}_j - \mu_1^{(j)}}{\sigma_1^{(j)}}\right) \\ &+ \lambda\left[\frac{1}{\sigma_0^{(i)}} \Phi'\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) \prod_{\substack{j=1 \\ j \neq i}}^{3} \Phi\left(\frac{\mathcal{T}_j - \mu_0^{(j)}}{\sigma_0^{(j)}}\right)\right], \qquad (i = 1, 2, 3), \end{aligned} \tag{19a}$$

where $\Phi'(x) \equiv d\Phi(x)/dx$ and

$$\prod_{i=1}^{3} \Phi\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) = (1-\alpha). \tag{19b}$$

Case 2: (MAJORITY rule) In accordance with this combining or voting rule, the collective decision produced at the data fusion center concerning the presence or absence of the bio-target is that made by more than half of the local detectors of the system (i.e., by at least two detectors in the case of a system of three detectors). For this decision strategy, the transition probabilities reduce to

$$F(\vec{D}) \equiv \Pr\{D_G = 1 | \vec{D}\} = \begin{cases} 1, & \text{if } |\vec{D}| \geq 2; \\ 0, & \text{otherwise;} \end{cases}$$

and

$$G(\vec{D}) \equiv \Pr\{D_G = 0 | \vec{D}\} = \begin{cases} 0, & \text{if } |\vec{D}| \geq 2; \\ 1, & \text{otherwise.} \end{cases}$$

Now, with reference to Eq. (14), we consider the maximization of the following Lagrange function:

$$\begin{aligned} L(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3) &= P_{\mathrm{D}} + \lambda[P_{\mathrm{FA}} - \alpha] \\ &= \sum_{i=1}^{3}(1 - P_{\mathrm{D}_i}) \cdot \prod_{\substack{j=1 \\ j\neq i}}^{3} P_{\mathrm{D}_j} + \sum_{i=1}^{3} P_{\mathrm{D}_i} \\ &\quad + \lambda\left[\sum_{i=1}^{3}(1 - P_{\mathrm{FA}_i}) \cdot \prod_{\substack{j=1 \\ j\neq i}}^{3} P_{\mathrm{FA}_j} + \sum_{i=1}^{3} P_{\mathrm{FA}_i} - \alpha\right]. \end{aligned}$$

Taking the partial derivative of L with respect $\mathcal{T}_i$ $(i = 1, 2, 3)$, setting the result to zero, and inserting the explicit expressions for P_{FA_i} and P_{D_i} [cf. Eqs (10a) and (12)] result in the following system of equations $(i = 1, 2, 3)$:

$$\begin{aligned} 0 = &-\frac{1}{\sigma_1^{(i)}}\Phi'\left(\frac{\mathcal{T}_i - \mu_1^{(i)}}{\sigma_1^{(i)}}\right) \cdot \sum_{\substack{j,k=1 \\ j,k\neq i \\ j\neq k}}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_j - \mu_1^{(j)}}{\sigma_1^{(j)}}\right)\right) \cdot \Phi\left(\frac{\mathcal{T}_k - \mu_1^{(k)}}{\sigma_1^{(k)}}\right) \\ &+ \lambda\left[-\frac{1}{\sigma_0^{(i)}}\Phi'\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) \cdot \sum_{\substack{j,k=1 \\ j,k\neq i \\ j\neq k}}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_j - \mu_0^{(j)}}{\sigma_0^{(j)}}\right)\right) \cdot \Phi\left(\frac{\mathcal{T}_k - \mu_0^{(k)}}{\sigma_0^{(k)}}\right)\right]. \end{aligned} \tag{20a}$$

This equation, when supplemented with the constraint,

$$\sum_{i=1}^{3} \Phi\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) \cdot \prod_{\substack{j=1 \\ j \neq i}}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_j - \mu_0^{(j)}}{\sigma_0^{(j)}}\right)\right) + \sum_{i=1}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right)\right) = \alpha, \qquad (20b)$$

permits the calculation of the local detection thresholds for optimum global detection performance.

Case 3: (AND rule) For this combining rule, the data fusion center decides H_1 only if all the local detectors decide H_1, so that the transition probabilities are given by

$$F(\vec{D}) \equiv \Pr\{D_G = 1 | \vec{D}\} = \begin{cases} 1, & \text{if } |\vec{D}| = 3; \\ 0, & \text{otherwise;} \end{cases}$$

and

$$G(\vec{D}) \equiv \Pr\{D_G = 0 | \vec{D}\} = \begin{cases} 0, & \text{if } |\vec{D}| = 3; \\ 1, & \text{otherwise.} \end{cases}$$

Substituting these transition probabilities into Eq. (14), the Lagrange function reduces to

$$\begin{aligned} L(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3) &= P_{\mathrm{D}} + \lambda\left[P_{\mathrm{FA}} - \alpha\right] \\ &= \prod_{i=1}^{3} P_{\mathrm{D}_i} + \lambda\left[\prod_{i=1}^{3} P_{\mathrm{FA}_i} - \alpha\right]. \end{aligned}$$

Now equating $\partial L / \partial \mathcal{T}_i$ $(i = 1, 2, 3)$ to zero leads to

$$\begin{aligned} 0 = &-\frac{1}{\sigma_1^{(i)}} \Phi'\left(\frac{\mathcal{T}_i - \mu_1^{(i)}}{\sigma_1^{(i)}}\right) \cdot \prod_{\substack{j=1 \\ j \neq i}}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_j - \mu_1^{(j)}}{\sigma_1^{(j)}}\right)\right) \\ &+ \lambda\left[-\frac{1}{\sigma_0^{(i)}} \Phi'\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right) \cdot \prod_{\substack{j=1 \\ j \neq i}}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_j - \mu_0^{(j)}}{\sigma_0^{(j)}}\right)\right)\right], \qquad (i = 1, 2, 3). \quad (21a) \end{aligned}$$

We need to solve these equations subject to the constraint

$$\prod_{i=1}^{3} \left(1 - \Phi\left(\frac{\mathcal{T}_i - \mu_0^{(i)}}{\sigma_0^{(i)}}\right)\right) = \alpha. \qquad (21b)$$

Since an analytical solution of the system of nonlinear algebraic equations for the optimal local detection thresholds is not possible, it is necessary to use a numerical method. Although the system of four equations in the four unknowns $\mathcal{T}_i$ $(i = 1, 2, 3)$ and λ is highly

nonlinear, this system of equations can, nevertheless, be readily solved using a quasi-Newton method that utilizes an appropriate line-search algorithm, as described by Dennis and Schnabel [6].

In order to provide some concrete results, we proceed to compare the achievable global detection performance of a distributed system of three local detectors with that provided by a single detector. In so doing, we will demonstrate the improvement of the detection performance of the distributed system of detectors over that provided by a single detector. For the numerical results, we consider a constant target aerosol signal $S(j) = S_0$ for $j = 1, 2, \ldots, J$, where J is the number of aerosol samples used in the detection procedure. For the simulations presented here, a constant bio-target signal S_0 was adjusted to provide the desired signal-to-noise ratio defined in accordance to Eq. (13). We have used a background aerosol clutter count with an intensity $\lambda^{(0)} = 10$. The detection performance for the distributed system using the three fusion rules (i.e., OR, MAJORITY, and AND rules) and for a single detector are compared in terms of the probability of detection (P_{D}) determined as a function of the signal-to-noise ratio (SNR) with both the sample size, J, (or, equivalently, detection time) and the probability of false alarm, P_{FA}, as implicit parameters. The numerical results are presented in Figs 1–9 for different values of these parameters. Each of these figures contains four detection performance curves, corresponding to either the single detector or the distributed system for one of the three combining strategies. These curves have been calculated for observation sample sizes of $J = 10$, 20, and, 30 and considered in combination with probabilities of false alarm of $P_{\mathrm{FA}} = 10^{-4}$, 10^{-3}, and 10^{-2}.

The following conclusions can be drawn from Figs 1–9. Firstly, since the detection performance curve for a single detector is always the lowest curve in these figures, the improved performance achieved with the distributed system is clearly noticeable. We see that for a given SNR, sample size, and false-alarm probability, the distributed system always performs better (in the sense of a higher detection probability) than the single detector. Secondly, as to be expected, the detection performance of the single and distributed detection system monotonically increases as the observation sample size, J, and/or the false-alarm probability, P_{FA}, increases. Thirdly, the detection performances of the distributed system for the three fusion rules considered are comparable for the larger observation sample sizes (e.g., for $J = 30$) and/or for the larger false-alarm probabilities (e.g., for $P_{\mathrm{FA}} = 10^{-2}$). Fourthly, for the smaller sample sizes and/or false-alarm probabilities, the detection performance of the distributed system is more strongly dependent on the fusion rule (combining strategy) used to combine the local detection decisions at the fusion center. Even so, it is

not possible to rank the fusion rules with respect to detection performance over the entire range of SNRs considered, since it is apparent that no single fusion rule is optimal over the complete SNR regime. However, a perusal of Figs 1–9 shows that the MAJORITY rule generally provides a better detection performance for a given set of conditions (e.g., fixed SNR, sample size, and false-alarm probability) than either the OR or AND rule for SNRs ranging from about −25 dB to −5 dB. Furthermore, the detection performance of the AND rule is superior to that of either the MAJORITY or the OR rule in the lower SNR regime (e.g., less than about −30 dB). Finally, the crossover point (in dB) at which the performance of one fusion rule is superior to that of another (in the sense of better detection performance) is a complex function of both the observation sample size and the false-alarm probability.

A clearer picture of the relative detection performances of the single detector and the distributed system for the three fusion rules can be obtained if we define a minimum detectable signal (MDS) in terms of the SNR (in dB) required to yield a detection probability $P_{\mathrm{D}} = 0.5$ for a fixed false-alarm probability, P_{FA}. The MDS has been computed as a function of P_{FA} values from 10^{-4} to 10^{-2}. These results are displayed in Fig. 10 for the single detector and for a distributed system using one of the three fusion rules considered above. An observation sample size of $J = 20$ has been used to evaluate the MDS. It is clear from Fig. 10 that the MDS can be used to rank the detection performance for the single detector and for the distributed system using one of the three fusion rules. Observe that the minimum detection performance of the distributed system is superior to that of the single detector. Furthermore, we note that in the case of a distributed system, the MAJORITY rule clearly exhibits superior minimum detection performance relative to either the AND or OR rule. Indeed, over the range of P_{FA} values considered, we determine a value of about 3.5 dB improvement in minimum signal detectability for a distributed system employing the MAJORITY rule over the single detector. The MAJORITY rule for the distributed system exhibits an MDS performance improvement of ≈ 0.5 dB and ≈ 3.0 dB over that provided by the AND rule and OR rule, respectively.

V. PLACEMENT OF DETECTORS IN A DISTRIBUTED SYSTEM

The concentration field arising from a BW agent source is inhomogeneous, non-isotropic, and time dependent as a result of the source configuration and the non-stationarity and inhomogeneity of the underlying atmospheric (environmental) flow. Because the BW agent cloud concentration is neither homogeneous nor isotropic, it is important to consider

the proper placement of the detectors in a distributed system in order to maximize detection performance.

As the BW agent puff-cloud passes over the target area, it is necessary to ensure that the individual detectors in the distributed system be located so that the detectors have a high probability of being inside the "core" of the BW agent cloud where the concentrations (and dosages) are high. Clearly, the proper choice of the number of samples, J, to use in the detection process, and the choice of thresholds $\mathcal{T}_i$ required to optimize the detection performance $P_{\rm D}$ of the system for a given SNR [cf. Eq. (13)], while ensuring simultaneously that a certain target probability of false alarm $P_{\rm FA}$ is never exceeded, is an extremely complex problem. The choice of the appropriate detection and false-alarm probabilities in a particular operational context is, of course, a question for military commanders to decide and one on which physical science has no bearing. But it needs to be stressed that (in general) operational standards cannot be based on $P_{\rm D} = 1$ with $P_{\rm FA} = 0$; it can never be absolutely guaranteed that the distributed system will provide perfect detection performance under any particular operating scenario. Once an operating point is decided upon (i.e., once $P_{\rm D}$ and $P_{\rm FA}$ have been chosen), the choice of J is set by the maximum allowable mean time to detection (viz., when a bio-target in some BW agent is encountered in the target area, the objective is to minimize the mean time to detection of the "threatening" bio-target so that appropriate countermeasures can be taken). The maximum allowable mean time to detection can be specified *a priori* based on operational considerations and this value can be used subsequently to determine an upper bound for J. With this choice of J, and given an operating point specified by $P_{\rm D}$ and $P_{\rm FA}$, receiver operating characteristic (ROC) curves similar to those exhibited in Figs 1–9 can be used to determine the SNR required to achieve this operating point for the distributed system. In some situations, such as long-range stand-off BW agent releases where the agent concentration at the detectors is small, the SNR required to achieve a particular operating point in the distributed system may not exist and the current methodology will fail to provide a solution in this case. This simply implies that the desired system performance cannot be achieved in this case, but even in this case, the methodology yields useful information in the sense that it provides the user with a specific prediction on when the detection system will fail.

The selection of J and SNR now permits the determination of the minimum dosage that needs to be acquired by the individual BW agent detectors in order achieve the target detection performance. In particular, the minimum required dosage can be determined from Eq. (13). Naturally, the minimum dosage level required for detection depends on the

background aerosol clutter count whose intensity is embodied in the parameter $\lambda^{(0)}$. It is assumed that the background has been characterized *a priori* (viz., the noise intensity parameter $\lambda^{(0)}$ for the operating environment is assumed to be known). The minimum dosage $\mathcal{D}_{\min}$ at each BW agent detector required to achieve the target detection performance can be determined as follows from Eq. (13):

$$\mathcal{D}_{\min} \equiv \sum_{j=1}^{J} S(j) = J\lambda_0 \cdot \mathrm{SNR}, \tag{22}$$

where the dosage $\mathcal{D}_{\min}$ must be achieved over the total sampling time $T \equiv J\tau$. To ensure that the individual BW agent detectors receive at least $\mathcal{D}_{\min}$ during the passage of a BW agent cloud over the target area, the detectors must be located in a region that will be covered with the threshold dosage $\mathcal{D}_{\min}$ or higher with a high probability.

The problem of the proper placement of BW agent detectors in order to achieve a certain global probability of detection for the distributed system now reduces to the problem of the determination of the locus of points in the target region where the dosage is equal to or greater than $\mathcal{D}_{\min}$, with some specified probability. In other words, we need to determine the statistical properties of the dosage and the fluctuating cloud concentration from which it is derived. To that purpose, we need to investigate the statistical properties of the partial dosage accumulated over a sampling (detection) time interval $T \equiv J\tau$, on exposure of a detector located at $\mathbf{x} \equiv (x, y, z)$ to the instantaneous concentration $\chi_s(\mathbf{x}, t)$ of the dispersing BW agent cloud:

$$\mathcal{D}(\mathbf{x}, T) = \int_0^T \chi_s(\mathbf{x}, t)\, dt. \tag{23}$$

In Eq. (23), it has been assumed without any fundamental loss of generality that the lower limit $t = 0$ corresponds to the time at which the detection interval began. The time origin $t = 0$ is then assumed to be reset for each new detection interval of duration T. Because $\chi_s(\mathbf{x}, t)$ is a random function, $\mathcal{D}(\mathbf{x}, T)$ must be a random (stochastic) integral. Hence, for a fixed point $\mathbf{x}$ and a fixed sampling time T, $\mathcal{D}(\mathbf{x}, T)$ is a random variable.

Naturally, the statistical properties of $\mathcal{D}$ must be determined by the probabilistic characteristics of the underlying cloud concentration fluctuations. The general probabilistic behavior of the random variable $\mathcal{D}$ can be expressed by its probability density function (PDF); and the essential statistical quantities that give information about the shape of this function are the values of the integral moments. Hence, if we define a PDF for the partial dosage $\mathcal{D}$ at position $\mathbf{x}$ over a sampling time T as

$$f(D; \mathbf{x}, T)\, dD = \Pr\{D \le \mathcal{D}(\mathbf{x}, T) < D + dD\}, \tag{24}$$

the k-th order integral moment of $\mathcal{D}$ is given by

$$\begin{aligned}\mu_k(\mathcal{D};T) \equiv \left\langle \mathcal{D}^k(T) \right\rangle &= \int_0^\infty D^k f(D;\mathbf{x},T)\,dD \\ &= \int_0^T \cdots \int_0^T \Big\langle \chi_s(t_1)\chi_s(t_2)\ldots\chi_s(t_k) \Big\rangle\, dt_1\,dt_2\ldots dt_k, \qquad k \in \mathbf{N}; \qquad (25a)\end{aligned}$$

or,

$$\begin{aligned}\mu_k'(\mathcal{D};T) \equiv \left\langle (\mathcal{D}(T)-\mu_1)^k \right\rangle &= \int_0^\infty (D-\mu_1)^k f(D;\mathbf{x},T)\,dD \\ &= \int_0^T \cdots \int_0^T \Big\langle \chi_s'(t_1)\chi_s'(t_2)\ldots\chi_s'(t_k) \Big\rangle\, dt_1\,dt_2\ldots dt_k, \qquad k \in \mathbf{N}, \qquad (25b)\end{aligned}$$

where the primes on a fluctuating quantity denote departures from the mean [e.g., $\chi_s'(t) \equiv \big(\chi_s(t) - \langle \chi_s(t) \rangle\big)$], and $\langle \ldots \rangle$ denotes an ensemble average (or, mathematical expectation). Here, the dosage is implicitly assumed to be determined at a fixed point so the explicit $\mathbf{x}$-dependence in Eqs (25a) and (25b) has been suppressed.

Note that the k-th order integral moments of the dosage $\mathcal{D}$ require complete information on the joint k-time point moments of the fluctuating cloud concentration $\chi_s(t)$. Hence, in order to obtain the statistical properties of $\mathcal{D}$, we require a complete knowledge of all the higher-order multi-time statistics of the fluctuating cloud concentration field. Unfortunately, very little information is currently available concerning the higher-order, multi-time point statistics of a cloud concentration field. In particular, only one- and two-time point statistics of the cloud concentration appear to have been measured or modelled. This information permits the determination of the two lowest-order moments of the dosage; namely, the mean and variance of $\mathcal{D}$ which we will consider briefly below.

In view of Equation (25a) evaluated for $k = 1$, the ensemble-mean dosage for a statistically non-stationary cloud (puff) release reduces to the following form:

$$\mu_1(\mathcal{D};T) \equiv \left\langle \mathcal{D}(T) \right\rangle = \int_0^T \Big\langle \chi_s(t) \Big\rangle\, dt. \qquad (26)$$

Equation (26) implies that the ensemble-mean dosage can be determined from only a knowledge of the ensemble-mean concentration of the BW agent cloud.

However, because the dosage is random owing to the fluctuating cloud concentration, it is necessary (at the very least) to also estimate the variance of the dosage in order to provide the simplest measure of the variability that can be expected in this quantity between

two realizations of the dispersion. Towards this objective, evaluation of Equation (25b) for $k = 2$ leads to the desired expression for the dosage variance:

$$\begin{aligned}\mu_2'(\mathcal{D};T) &\equiv \langle \mathcal{D}'^2(T)\rangle \\ &= \int_0^T \int_0^T \Big\langle \chi_s'(t_1)\chi_s'(t_2)\Big\rangle\, dt_1\, dt_2 \\ &= 2\int_0^T \Big\langle {\chi_s'}^2(t_1)\Big\rangle\, dt_1 \int_0^{t_1} \rho(\chi_s; t_1, s)\, ds;\end{aligned} \tag{27a}$$

where

$$\rho(\chi_s; t, \tau) \equiv \frac{\langle \chi_s'(t)\chi_s'(\tau)\rangle}{\langle {\chi_s'}^2(t)\rangle}, \tag{27b}$$

is the autocorrelation function for the $\chi_s(t)$ random process; t and τ are diffusion times. Hence, $(t-\tau)$ corresponds to the correlation lag time. We note that the concentration of a diffusing cloud measured at a fixed point in space does not constitute a stationary process with the result that its autocorrelation function is a function of two diffusion times, t and τ [or, equivalently, of a diffusion time t and a lag time $(t-\tau)$].

We now express the dosage variance as follows:

$$\begin{aligned}\Big\langle \mathcal{D}'^2(T)\Big\rangle &= 2\int_0^T \Big\langle {\chi_s'}^2(t_1)\Big\rangle\, dt_1 \int_0^{t_1} \rho(\chi_s; t_1, s)\, ds \\ &= 2\int_0^T \Big\langle {\chi_s'}^2(t)\Big\rangle T_\chi(t)\, dt,\end{aligned} \tag{28}$$

where $T_\chi(t)$ is the integral time scale for the $\chi_s(t)$ process at the diffusion time t:

$$T_\chi(t) \equiv \int_0^t \rho(\chi_s; t, s)\, ds. \tag{29}$$

Thus, in order to calculate the dosage variance, we need an estimate of the integral time scale of concentration fluctuations. A simple estimate of $T_\chi(t)$ has been provided by Sykes [7] who used Gifford's [8] meandering plume model to provide a simple scheme for estimating T_χ of plume concentration from a knowledge of the Eulerian velocity time scale. This analysis showed that the effect of intermittency is to reduce the integral time scale of concentration fluctuations from the Eulerian wind fluctuation time scale, and also to introduce a logarithmic correction factor that depends on the relative fluctuation intensity (i.e., standard deviation of concentration divided by mean concentration) of the concentration fluctuations.

Given a model for the ensemble-mean concentration, concentration variance, and integral time scale of concentration fluctuations, it is now possible to determine the mean

and variance of the dosage using Eqs (26) and (28), respectively. Unfortunately, the dosage $\mathcal{D}(T)$ cannot really be adequately described in terms of the ensemble-mean dosage and dosage variance without also specifying the form of the dosage PDF. Our current knowledge of cloud concentration statistics do not enable us to predict an exact form for the dosage PDF (i.e., the latter would effectively require explicit knowledge of the multi-time point, higher-order statistics of the cloud concentration field). In consequence, to make further progress the only recourse we have available at present is to compare dosage data, derived from measured atmospheric concentration time series, to some common functional forms for model PDFs. To that end, it should be mentioned that analysis of a large number of plume concentration time series measured in the cooperative Concentration Fluctuation Experiments (CONFLUX) project [9–11] has shown that the dosage PDF can be approximated reasonably well by the clipped-normal PDF form for sampling times T greater than about 5 s [12]. In particular, when the clipped-normal PDF is fitted to the dosage data derived from the fluctuating plume concentration, it appears to represent most features of the statistics of the data (e.g., various higher-order moments of the dosage, quantiles of the dosage, etc.) quite well, at least for exposure (averaging) times $T \gtrsim 5$ s. In this regard, it should perhaps be noted that the effect of smoothing (i.e., by increasing the averaging or sampling time over which the dosage is determined) generally tends to improve the fit of the clipped-normal distribution to the random dosage compared to that of the underlying fluctuating concentration process from which it was derived.

In consequence, the dosage PDF will be assumed to be adequately modelled using a clipped-normal PDF which is defined as follows:

$$f(D;\mathbf{x},T) = \frac{1}{\sqrt{2\pi}\sigma_D} \exp\left(-\frac{1}{2}\left(\frac{D-\mu_D}{\sigma_D}\right)^2\right) + (1-\gamma)\delta(D), \tag{30}$$

where

$$\gamma \equiv \frac{1}{2}\left(1 + \operatorname{erf}\left(\frac{\mu_D}{\sqrt{2}\sigma_D}\right)\right), \tag{31}$$

and μ_D and σ_D are location and scale parameters, respectively. In Eq. (31), erf$(\cdot)$ denotes the error function. In the clipped-normal PDF, a Gaussian PDF is used to model the continuous part of the distribution of $\mathcal{D}$ for $\mathcal{D} > 0$, with the probability of negative dosages being transferred into a delta function at $\mathcal{D} = 0$ to represent the intermittency effect. In the clipped-normal PDF, the intermittency factor γ is uniquely determined as a function of μ_D/σ_D. Also, the two parameters μ_D and σ_D, which completely define the clipped-normal PDF, can be uniquely determined from the mean dosage, $\langle\mathcal{D}(T)\rangle$, and dosage variance,

$\langle \mathcal{D}'^2(T) \rangle$, using the following two relationships:

$$\langle \mathcal{D}(T) \rangle = \frac{\sigma_D}{\sqrt{2\pi}} \exp\left(-\frac{\mu_D^2}{2\sigma_D^2}\right) + \gamma\mu_D, \tag{32}$$

and

$$\langle \mathcal{D}'^2(T) \rangle = -\langle \mathcal{D}(T) \rangle^2 + \sigma_D\gamma + \mu_D \langle \mathcal{D}(T) \rangle, \tag{33}$$

where γ is defined in Equation (31).

We may now exploit the information contained in the statistical description of the partial dosage for the proper placement of individual BW agent detectors in a distributed system in order to satisfy certain constraints on the global detection probability for a fixed false-alarm rate with a prescribed allowable maximum mean time to detection. These constraints can be met if the individual BW agent detectors are placed at points in the target region where the dosage is greater than or equal to a "critical" or "threshold" dosage $\mathcal{D}_{\min}$ prescribed in Eq. (22). In other words, for a prescribed "critical" or "threshold" dosage $\mathcal{D}_{\min}$, we are interested in the determination of the points in the target region where the dosage received in a particular sampling (detection) interval at least equal to $\mathcal{D}_{\min}$, with some specified probability. The goal is to place the individual BW agent detectors of the distributed system within an area of the target region that will be well covered to at least the critical dosage $\mathcal{D}_{\min}$ over a given sampling (detection) time.

In view of Eq. (30), the value of $F(D; \mathbf{x}, T)$ where

$$F(D; \mathbf{x}, T) \equiv \int_D^\infty f(D'; \mathbf{x}, T)\, dD', \tag{34}$$

is the probability that any one realization of the ensemble of the partial dosages, accumulated over sampling time T at $\mathbf{x}$, is greater than D. Alternatively, it is the proportion of realizations in the whole ensemble of BW agent clouds for which the partial dosage $\mathcal{D}$ received in a particular sampling (detection) time T and at location $\mathbf{x}$ is greater than D. The equation

$$F(D; \mathbf{x}, T) = \alpha, \tag{35}$$

where α is a fixed constant between zero and one [i.e., $\alpha \in (0, 1)$] is, for a particular sampling time T, a surface at every point of which there is a probability α that the partial dosage $\mathcal{D}$ obtained in duration T exceeds D. For every point outside the surface, the probability that the partial dosage accumulated in a sampling time T exceeds D is less than α. Furthermore, for fixed T, each point in space is associated with just one value of α so that it lies on a unique surface of the family of surfaces that is specified by Eq. (35). Each of these surfaces

intersects the plane $z_s = k$ (k is a constant) in a curve or contour. Here, z_s refers to the height of the detectors above the ground surface. To ensure a high probability of detection for the distributed system, the individual BW agent detectors should be placed within that contour for which the dosage level is at least the "critical" or "threshold" dosage $\mathcal{D}_{\text{min}}$ prescribed in Eq. (22).

VI. SUMMARY AND CONCLUSIONS

In this report, we have presented a methodology for the design and placement of BW agent detectors in a distributed system. The first step of the methodology involves the modelling of the detection performance of the individual detectors. In the regard, we have focussed on the generalized likelihood ratio algorithm based on a Poisson probability model for binary hypothesis testing. This model is used to describe the counting statistics associated with the detection of a bio-target signal embedded in a common aerosol clutter background. By using asymptotic normal theory, the approximate distribution of the detection statistic (viz., the log-likelihood ratio in this case) has been derived. We showed how this can be used to predict the probability of detection for a prescribed probability of false alarm as a function of the threshold level, the signal-to-noise ratio of the detection environment, and the total number of samples used for the detection.

The second step of the methodology concerns the design and characterization of the combining strategy that will be used to provide the final global detection decision. For a given BW agent remote detection scenario, the detection and false-alarm probabilities for each local detector in the distributed system can be expressed explicitly in terms of its thresholds and operating SNRs. These expressions can be substituted into a set of n equations for the optimum thresholds derived in Section III. This results in a set of n equations in the n unknown thresholds. These equations involve a common undetermined (Lagrange) multiplier λ. Together with the overall target false-alarm probability constraint $P_{\text{FA}} = \alpha$, where P_{FA} is given in Eq. (16), the resulting design equations may be solved numerically for the optimum thresholds for a given combining strategy at the data fusion center. The overall system detection performance, P_{D}, can then be evaluated. When this procedure has been carried out for all the combining strategies at the data fusion center and for a given set of operating SNRs, we then choose that strategy which results in the best performance. The constraint imposed by the operating SNRs can be achieved by the correct placement of the local detectors, which constitutes the third and final step of the methodology.

Explicit results are provided for the specific case of a distributed system of three detectors with the fusion rule at the data fusion center based on the k-out-of-n logical function. For the case of a distributed system of three detectors (i.e., $n = 3$), this logical function provides the OR rule ($k = 1$), the MAJORITY rule ($k = 2$), and the AND rule ($k = 3$). Numerical results of the global detection performance of the distributed system for these three fusion rules are provided and this performance is compared to that achievable with a single detector. The numerical simulations and results indicate that, for a given set of operating conditions (e.g., signal-to-noise ratio, sample size, and false-alarm probability), the distributed system always exhibits better detection performance (e.g., in the sense of a higher detection probability) than that afforded by a single detector. Furthermore, we showed that for the distributed system, no single fusion rule appears to provide an optimal detection performance over the entire range of SNRs. It has been observed that the order of detection performance of the distributed detector system, under the various fusion rules used, is a complex function of the signal-to-noise ratio, the number of observations used in the detection process, and the probability of false alarm. With an increase in the sample size, J, (or, equivalently, an increase in the sampling time) and/or an increase in the tolerable false-alarm probability, the detection performance of both the single detector and the distributed system improved. Furthermore, with an increase in the sample size and/or allowed false-alarm probability, the differences in performance of the various combining strategies (fusion rules) narrow.

The third step of the methodology involves the correct placement of the individual detectors in the distributed system over the target area. The selection of sample size, J, which in turn is determined by the maximum allowable mean time to detection, and of the operating signal-to-noise ratio permits the determination of the minimum dosage level that needs to be acquired by the individual (peripheral) BW agent detectors in order that the overall system achieve a target global detection performance. In particular, the target detection performance for the distributed system can be met if the individual BW agent detectors can be placed at points in the target region where the dosage level reaches at least a "critical" or "threshold" dosage $\mathcal{D}_{\min}$ [cf. Eq. (22)]. This requires the determination of the points in the target region where the dosage received in a particular sampling (detection) time is equal to or higher than $\mathcal{D}_{\min}$, with some specified probability. In consequence, a model for the ensemble mean dosage and dosage variance has been derived that allows these quantities to be determined from an explicit knowledge of the mean concentration, concentration variance, and an integral time scale of concentration fluctuations for the dispersing BW agent cloud. It is important to note that there currently exists a practical

probabilistic model for turbulent diffusion [i.e., the Second-Order Closure Integrated PUFF (SCIPUFF) model [13] developed by Aeronautics Research Associates Princeton (ARAP) under the sponsorship of Defence Special Weapons Agency (DSWA)] that is capable of providing estimates for the mean concentration, concentration variance, and an integral time scale of concentration fluctuations. The incorporation of the proposed methodology for detector placement within SCIPUFF will permit then a completely probabilistic or statistical approach to the correct placement of individual BW agent detectors in a distributed system for a given BW agent release scenario.

VII. REFERENCES

1. "Report of the Quadrennial Defense Review", Department of Defense Report, May, 1997.

2. "Proliferation: Threat and Response 1997", Department of Defense Report, November, 1997.

3. Pinnick, R. G., Hill, S. C., Nachman, P., Pendleton, J. D., Fernandez, G. L., Mayo, M. W., and Bruno, J. G., "Fluorescence Particle Counter for Detecting Airborne Bacteria and Other Biological Particles", Aerosol Science and Technology, 23, pp. 653–664, 1995.

4. Helstrom, C. W., *Statistical Theory of Signal Detection*, Elmsford, New York: Pergamon, 1968.

5. Feller, W., *An Introduction to Probability Theory and Its Applications*, New York: John Wiley & Sons, Inc., 1957.

6. Dennis, Jr., J. E. and Schnabel, R. B., *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Englewood Cliffs, New Jersey: Prentice-Hall, 1983.

7. Sykes, R. I., "The Variance in Time-Averaged Samples from an Intermittent Plume", Atmospheric Environment, 18, pp. 121–123, 1984.

8. Gifford, F. A., "Statistical Properties of a Fluctuating Plume Dispersion Model", Advances in Geophysics, 6, pp. 117–137, 1959.

9. Yee, E., Kosteniuk, P. R., Chandler, G. M., Biltoft, C. A., and Bowers, J. F., "Statistical Characteristics of Concentration Fluctuations in Dispersing Plumes in the Atmospheric Surface Layer", Boundary-Layer Meteorology, 65, pp. 69–109, 1993.

10. Yee, E., Chan, R., Kosteniuk, P. R., Chandler, G. M., Biltoft, C. A., and Bowers, J. F., "Experimental Measurements of Concentration Fluctuations and Scales in a Dispersing Plume in the Atmospheric Surface Layer Obtained Using a Very Fast Response Concentration Detector", Journal of Applied Meteorology, 33, pp. 996–1016, 1994.

11. Yee, E., Chan, R., Kosteniuk, P. R., Chandler, G. M., Biltoft, C. A., and Bowers, J. F., "The Vertical Structure of Concentration Fluctuation Statistics in Plumes Dispersing in the Atmospheric Surface Layer", Boundary-Layer Meteorology, 76, pp. 41–67, 1995.

12. Yee, E. and Chan, R., "Statistical Characteristics of the Non-linear Toxic Load Derived for Fluctuating Concentrations in a Plume Dispersing in the Atmospheric Surface Layer", Atmospheric Environment (in preparation), 1997.

13. Sykes, R. I., "PC-SCIPUFF Version 0.2: Technical Documentation", A.R.A.P. Report No. 712, Titan Corporation, Princeton, NJ, 1995.

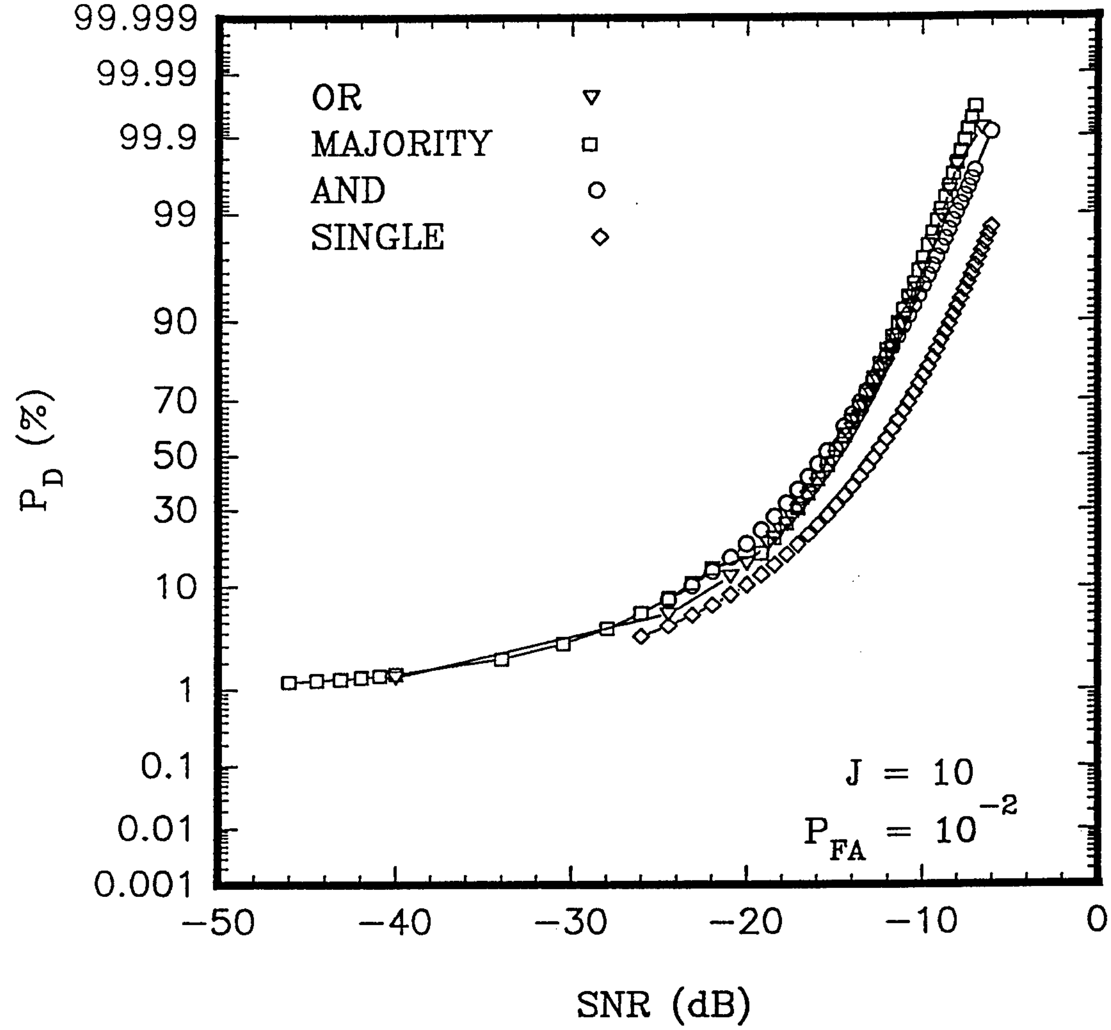

Figure 1

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 10$ and $P_{FA} = 10^{-2}$.

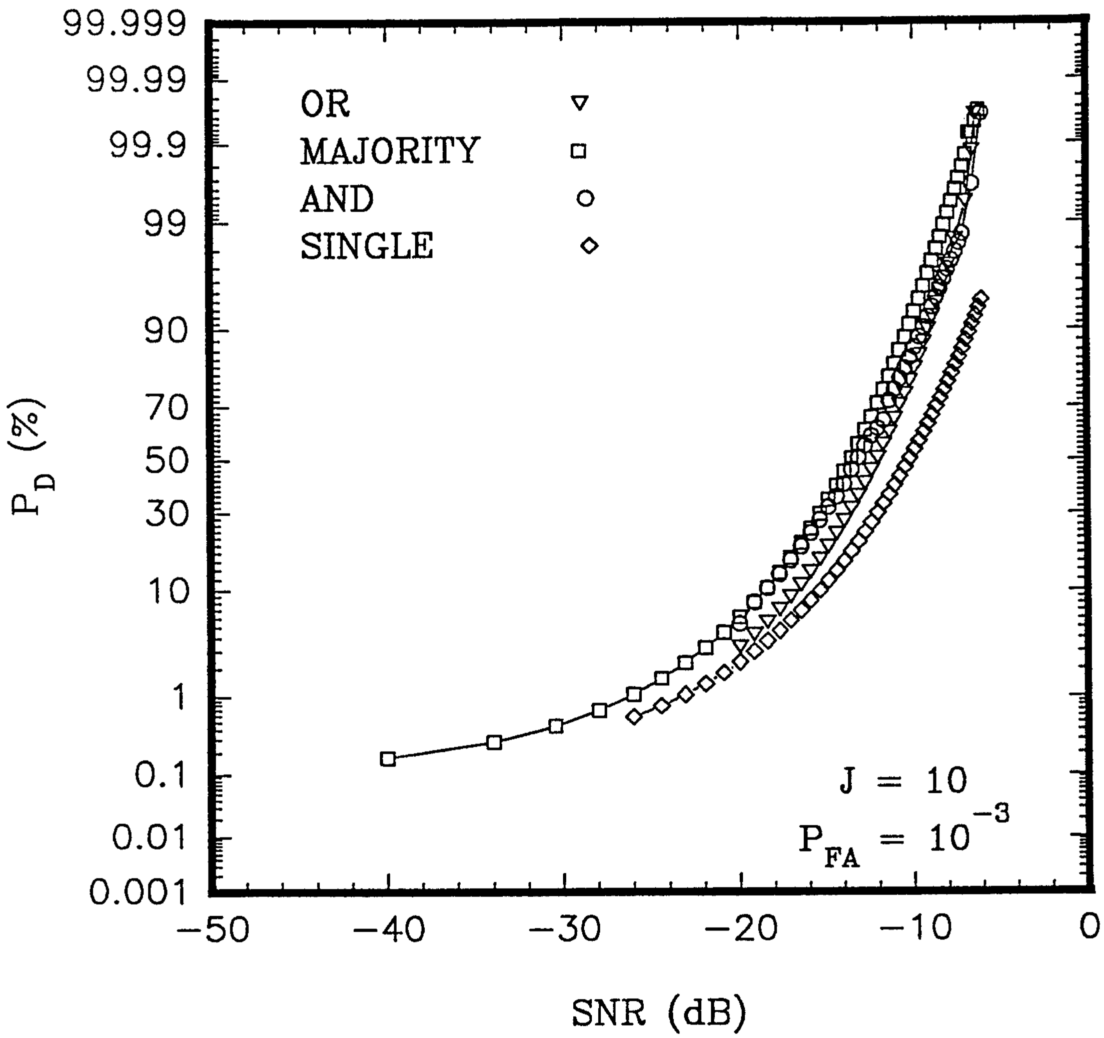

Figure 2

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 10$ and $P_{FA} = 10^{-3}$.

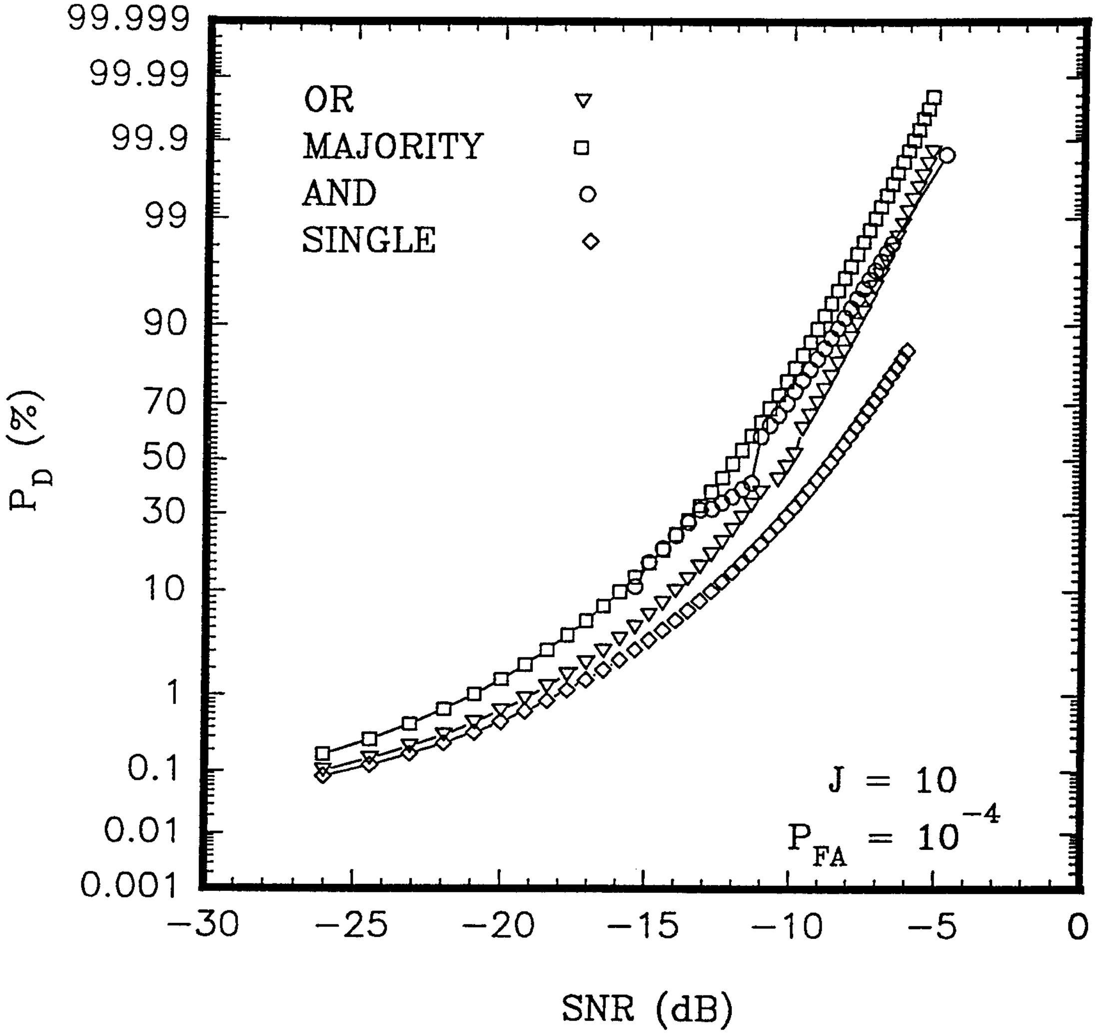

Figure 3

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 10$ and $P_{FA} = 10^{-4}$.

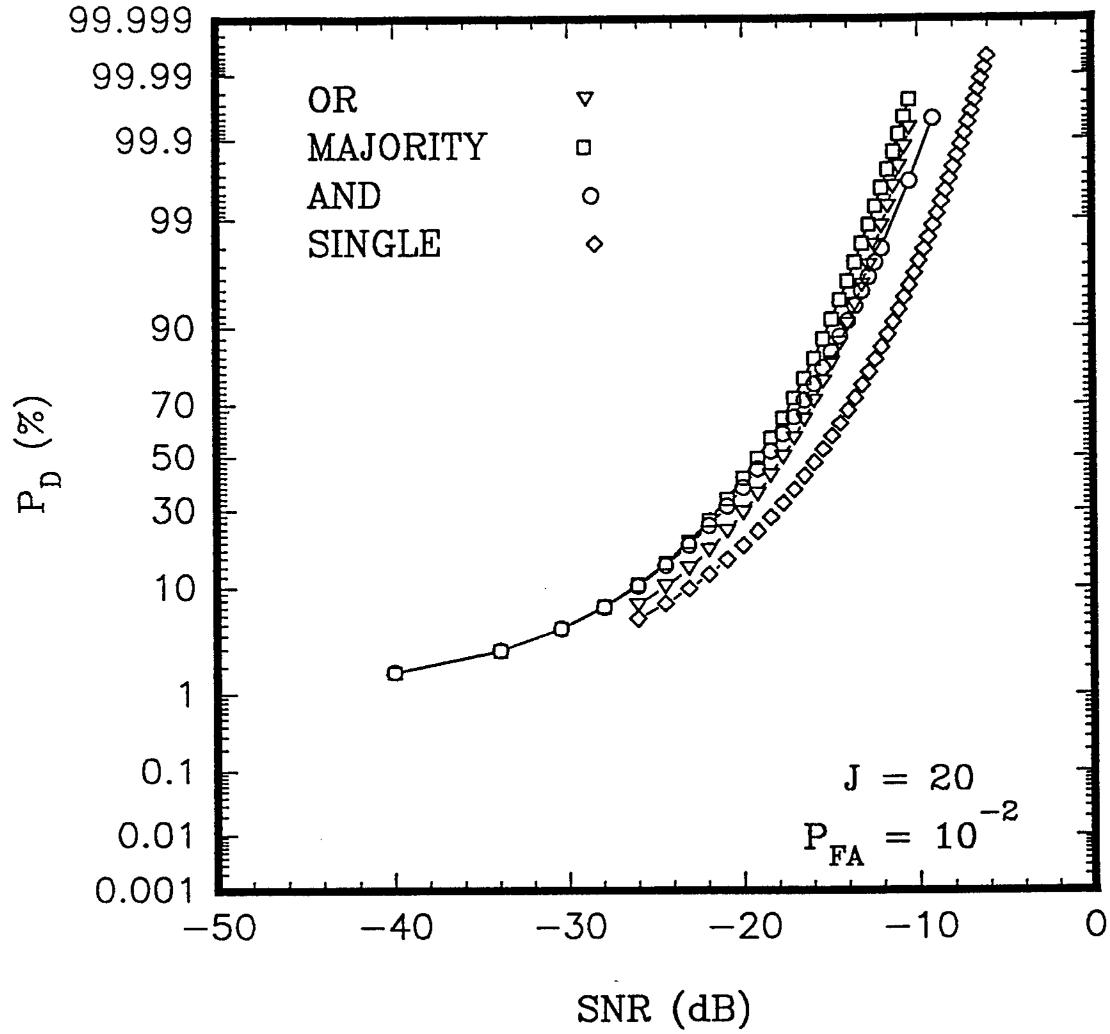

Figure 4

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 20$ and $P_{FA} = 10^{-2}$.

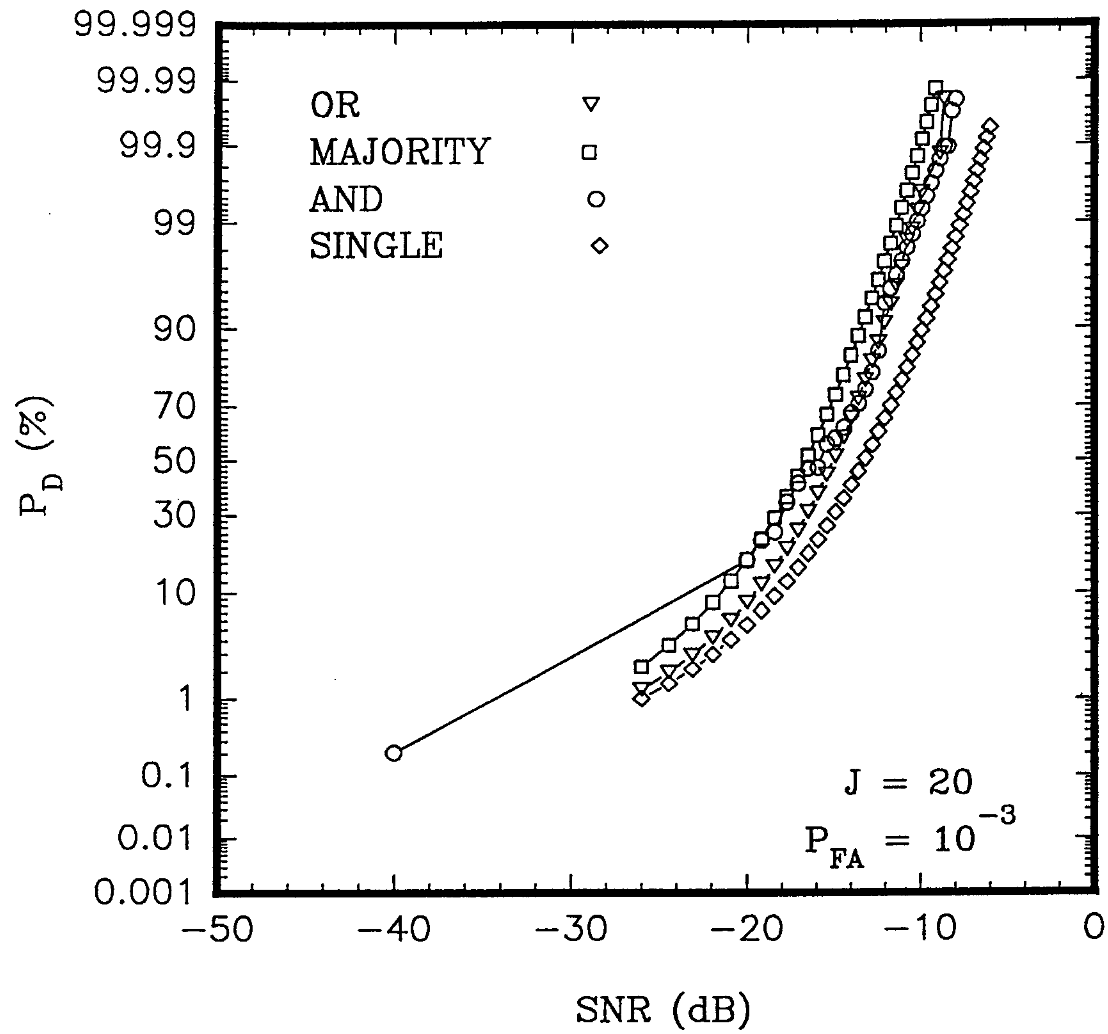

Figure 5

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 20$ and $P_{FA} = 10^{-3}$.

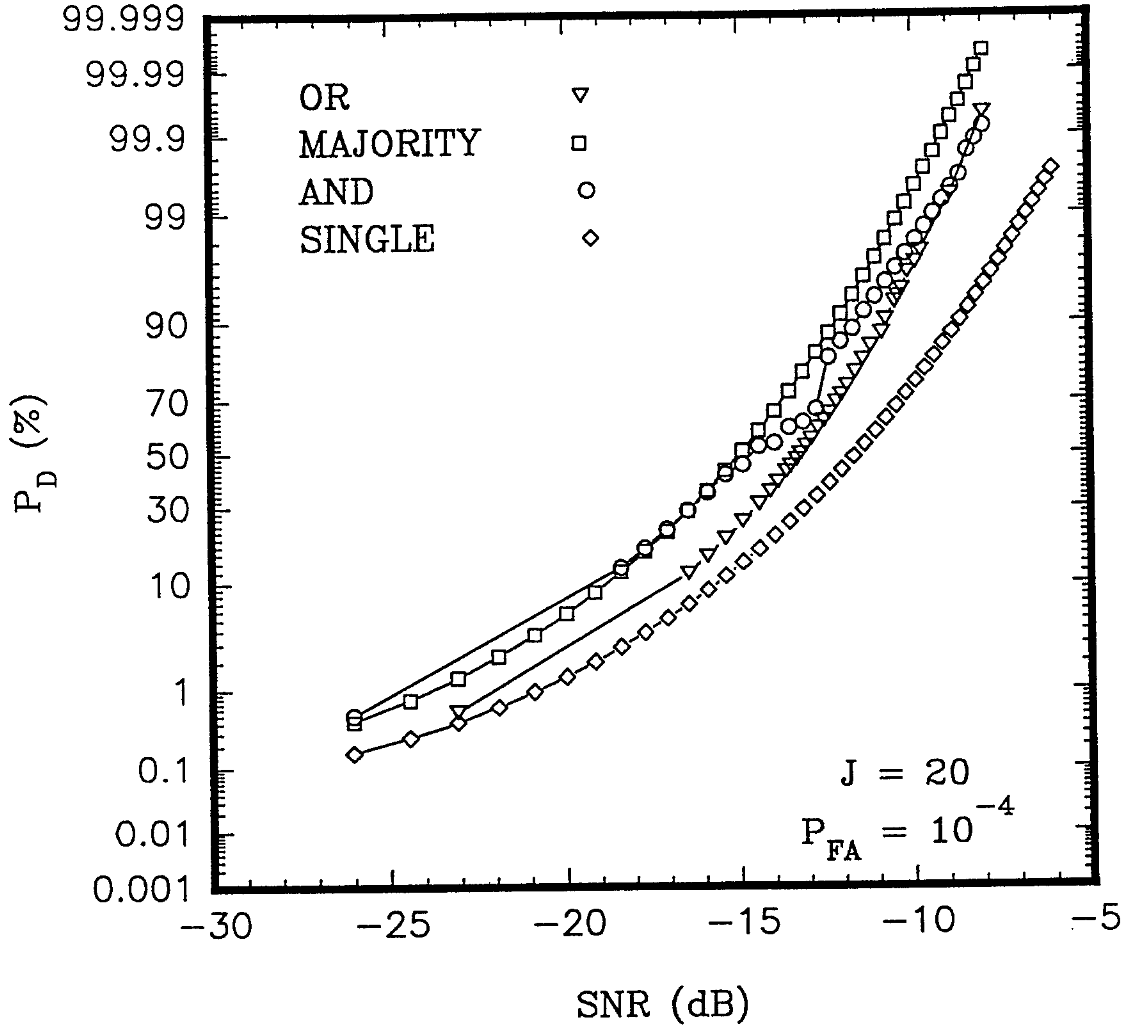

Figure 6

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 20$ and $P_{FA} = 10^{-4}$.

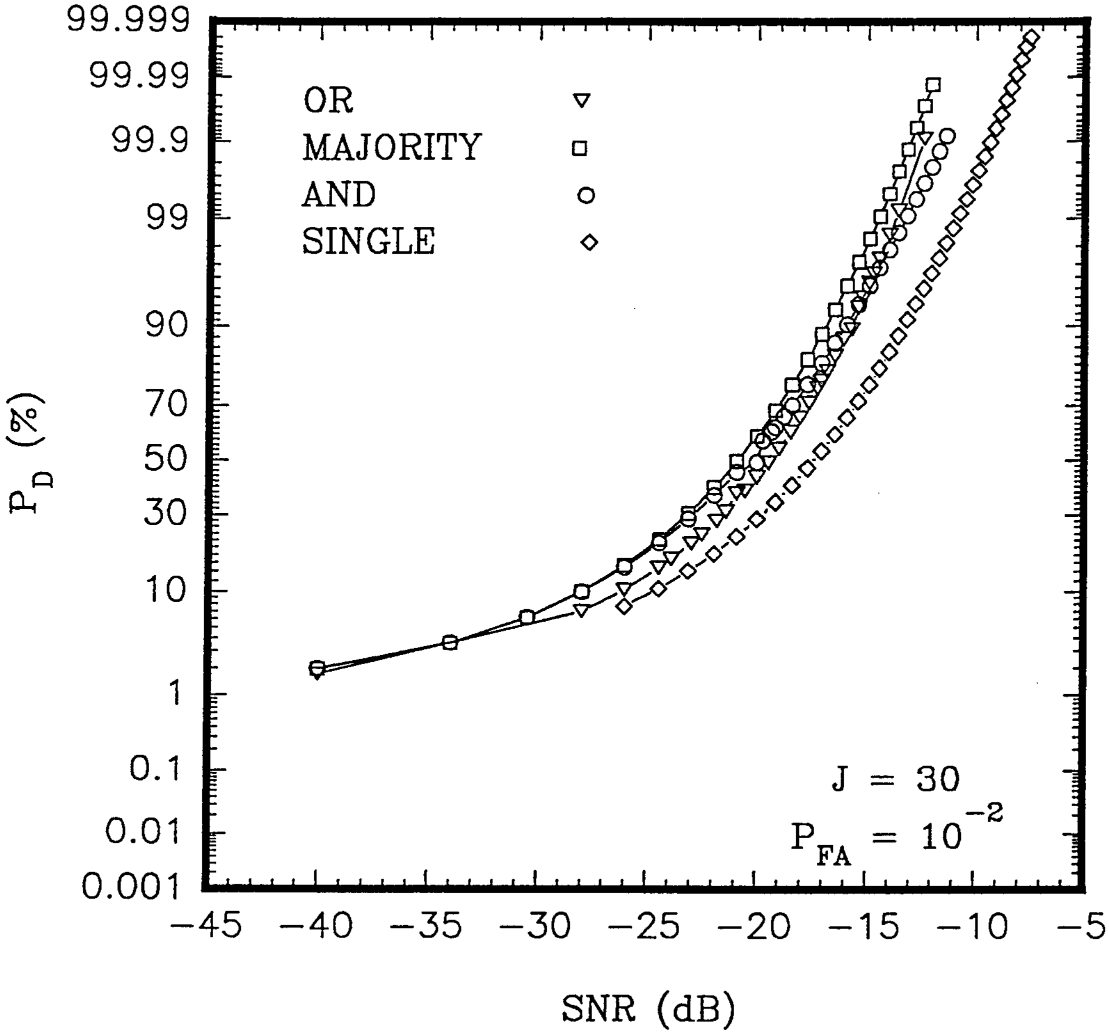

Figure 7

Detector performance comparison (expressed as the probability of detection, P_{D}, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 30$ and $P_{\mathrm{FA}} = 10^{-2}$.

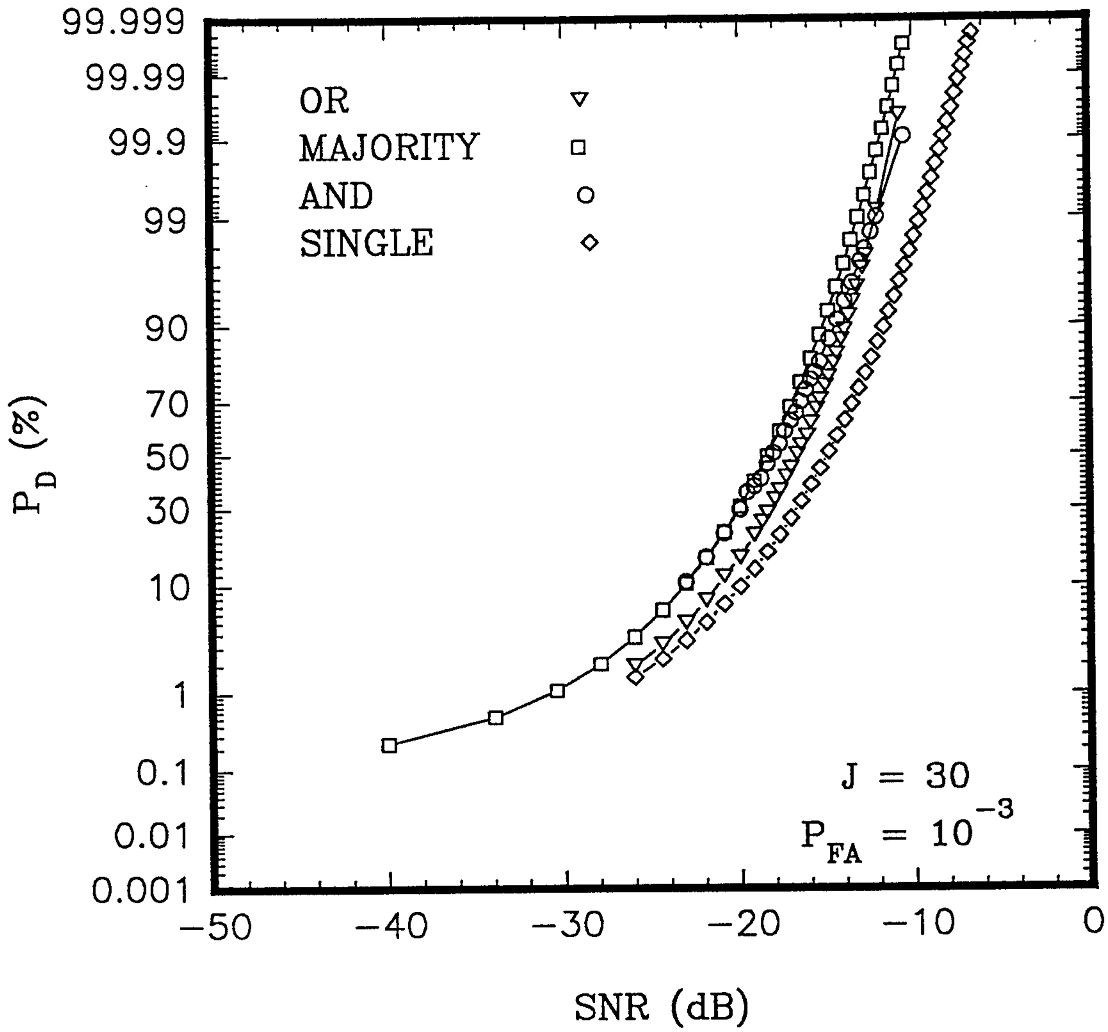

Figure 8

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 30$ and $P_{FA} = 10^{-3}$.

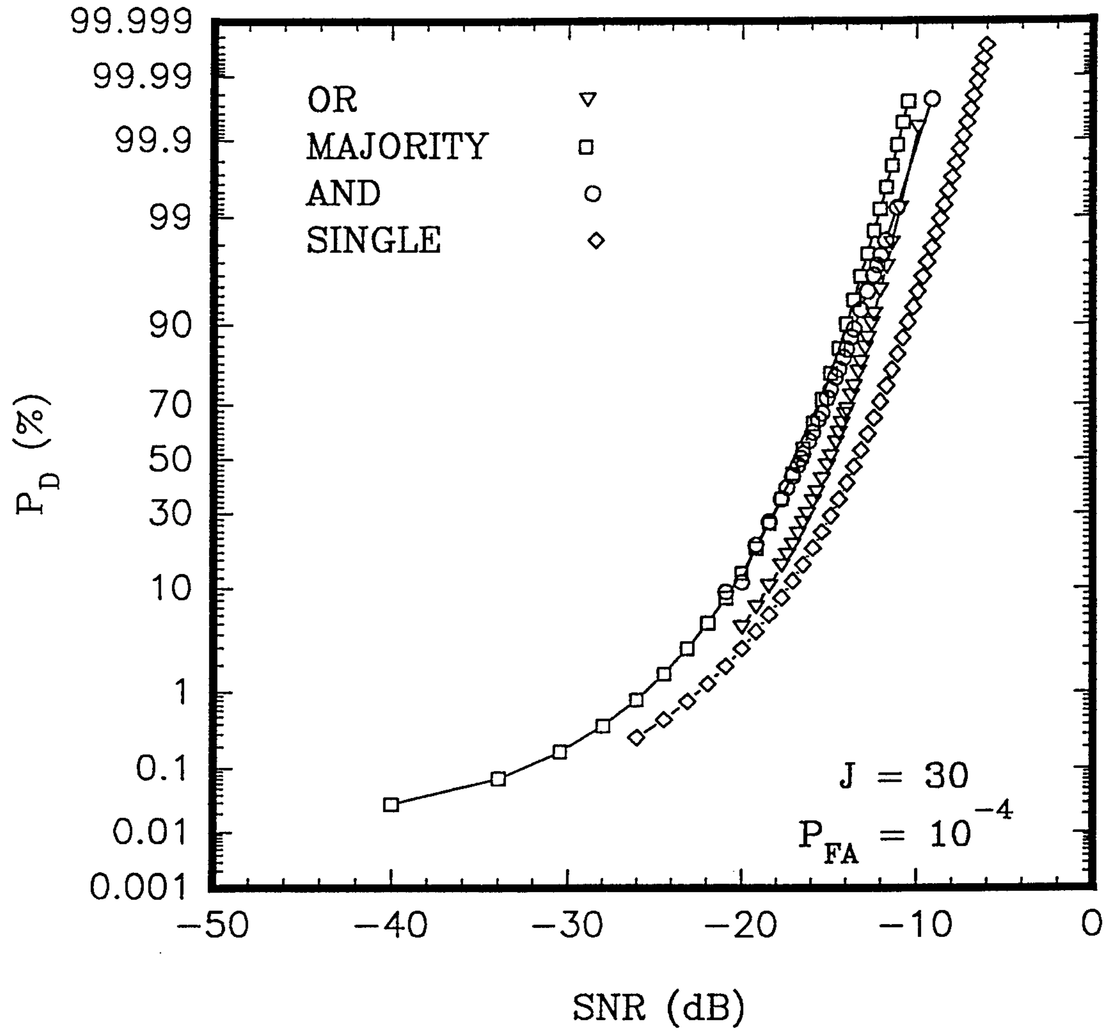

Figure 9

Detector performance comparison (expressed as the probability of detection, P_D, versus SNR) of a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector for $J = 30$ and $P_{FA} = 10^{-4}$.

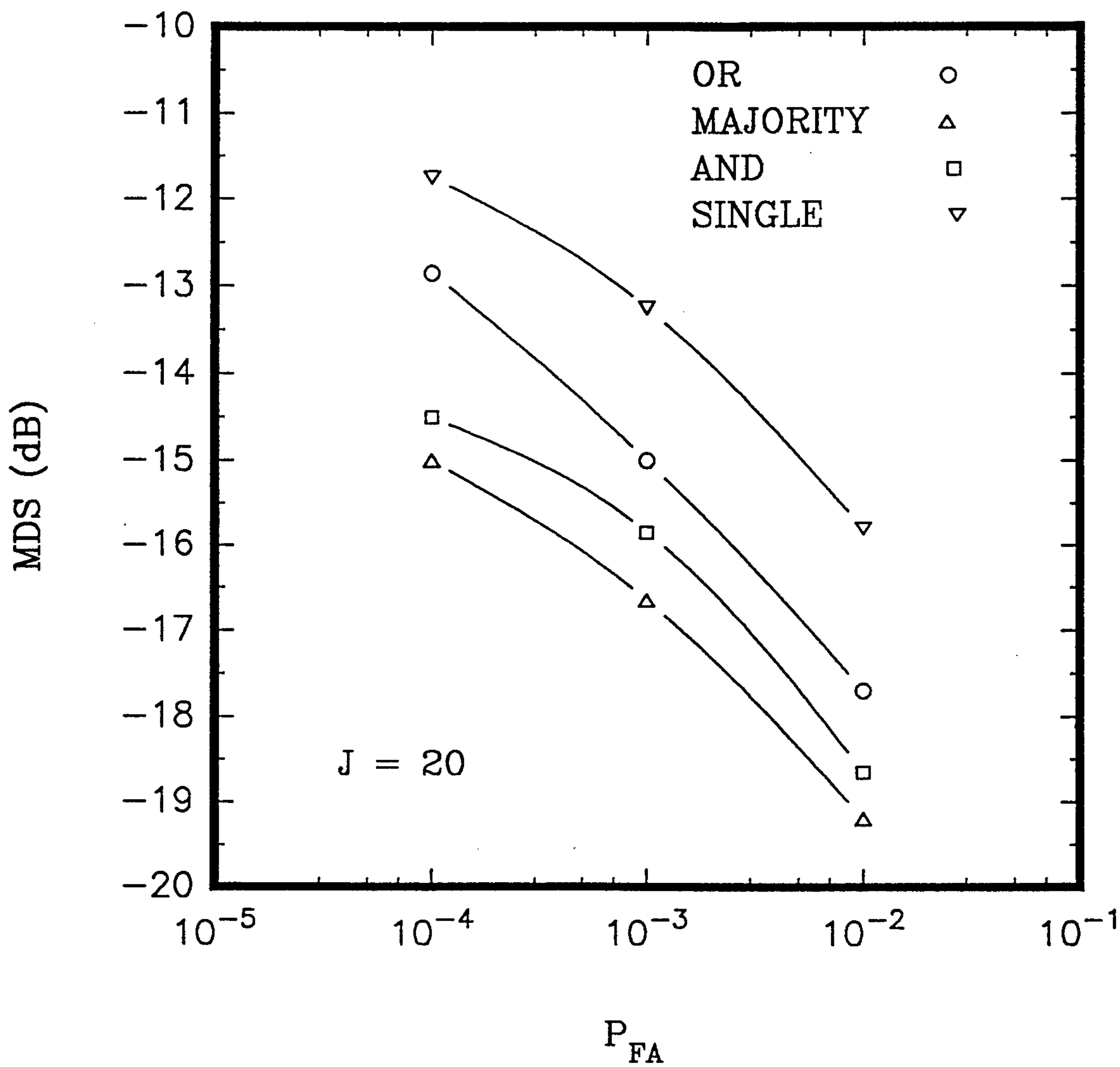

Figure 10

The minimum detectable signal (MDS) versus the probability of false alarm, P_{FA}, for a distributed system composed of three detectors using the OR, MAJORITY, and AND fusion rules at the central processor and of a single detector.

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This report deals with the design and performance evaluation of a distributed detection system for a dispersing biological warfare (BW) cloud embedded in the natural aerosol component of the background air. The distributed system employs a number of physically separated BW agent point detectors (sentries) located within some target region and a data fusion center that provides the final decision as to the presence or absence of the bio-target by combining the individual localized decisions from the various point detectors using a prespecified combining strategy. In this system, each detector implements a generalized likelihood ratio test on its own localized observations to test for the presence or absence of a bio-target. These localized detection decisions are then transmitted to a data fusion center where they are logically combined to yield a global detection decision for the distributed system. The optimization of the global detection performance of the distributed system is derived by application of the Lagrange multipliers method, whereby the global probability of detection for the system is maximized subject to the constraint that the global probability of false alarm is maintained at a prespecified level (viz., at a constant and tolerable false-alarm rate). A number of combining strategies are investigated in order to determine some overall system optimality for detection. It is found that the optimal detection strategy for each individual BW agent detector in the distributed system depends on the strategy of all the other detectors, as well as on the structure of the data fusion center. Explicit numerical results, in the form of the probability of detection versus signal-to-noise ratio for several preassigned false-alarm probabilities and sample sizes [which determine the maximum allowable mean time to detection], are presented for the case of a distributed system consisting of three BW agent detectors. The results are compared to the detection performance that is achievable using only a single detector. Finally, the problem of the correct placement of the individual BW agent detectors in the distributed system in order to achieve a specified detection performance is addressed. In particular, a method for the determination of the dosage probabilities at fixed points in the target region is developed and used to place BW agent detectors in a distributed system.

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